A COMPREHENSIVE PSYCHOMETRIC AUDIT OF AN EXISTING SELECTION PROCEDURE

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DECLARATION

I, the undersigned, hereby declare that the work contained in this thesis is my own original work and that I have not previously in its entirety or in part submitted it at any university for a degree.

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ABSTRACT

Selection represents a critical human resource intervention by virtue of its ability to regulate the movement of employees into, through and out of the organisation. Selection thus represents a relatively visible mechanism through which access to employment opportunities can be regulated. From the perspectives of both affirmative action and fairness, as well as utility, selection has therefore been under intense scrutiny. This implies that there are two substantial criteria in terms of which selection procedures need to be evaluated, namely equity and efficiency. Should the human resource function be challenged to defend its selection procedure, it should be able to assemble credible evidence to show the efficiency and equity of the disputed intervention by means of a reasoned justification. The problem is, however, that most selection procedures being operated in South Africa would probably not be able to successfully meet this burden of persuasion. The search for equitable and efficient selection procedures thus necessitates the need for psychometric audits to provide the feedback required to adjust selection procedures towards greater efficiency and equity, and to provide the evidence required for the vindication of organisations should they be challenged in terms of the South African anti-discriminatory labour legislation.

The Guidelines for the Validation and Use of Selection Procedures developed by the Society for Industrial Psychology (1998) represents an attempt to illustrate the ideal process according to which selection procedures should be developed and validated. Conditional on the acceptance that the Guidelines (1998) set out the most justifiable methodology for the development and justification of selection procedures, it becomes a necessity for organisations to periodically evaluate (i.e. periodically psychometrically audit) their current selection procedures and its developmental history to determine whether the human resource function can convincingly demonstrate:

- The business necessity of the selection procedure;
- The validity of the performance theory on which the selection procedure is based; and
- That the selection strategy combines applicant information fairly.

A checklist was developed from relevant psychometric literature for the purpose of the psychometric audit representing a structured list of activities required to justify the use of a selection procedure. A psychometric audit was conducted on a selection procedure for call centre staff of a large SA insurance company. The audit uncovered a number of deficiencies in the call center selection procedure and its developmental history.

The performance hypothesis, in which the choice of operational predictor measures is grounded, was neither developed, nor argued, nor documented with sufficient clarity to indicate unambiguously the presumed nature of the nomological network of performance determinants and performance constructs. Problems were found with the external validity of the validation design. No reliability, validity, fairness or utility analyses had been performed at the time of the audit.

Subsequent correlation analysis indicates low statistically insignificant correlations between the majority of the chosen predictors and the developed criteria. Nonetheless, linear combinations of predictors were found for each of the three call center positions that significantly explain moderate proportions of criterion variance. The fairness of the use of the CSR multiple regression equation across black and white applicants was examined and found to be acceptable. Due to practical constraints, the utility of the selection procedure has not been evaluated.

It is recommended that the current selection procedure be re-examined in detail by the company to bring about positive changes in the performance hypothesis and the operational criterion measures. Thereafter, concrete evidence of reliably generated methodological research needs to be obtained again in order to verify the appropriateness, reliability and the meaningfulness of the inferences made from predictor assessments, thereby limiting, if not eliminating, possible cases of litigation.

OPSOMMING

Seleksie verteenwoordig 'n kritieke menslikehulpbronintervensie omdat dit die vermoë het om die beweging van werknemers in, deur en uit 'n organisasie te reguleer. Seleksie verteenwoordig dus 'n relatief sigbare meganisme waarmee toegang tot werksgeleenthede gereguleer word. Uit die oogpunt van sowel regstellende aksie as regverdigheid, en ook bruikbaarheid, is seleksie tans geweldig onder die vergrootglas. Hiermee word geïmpliseer dat die twee substansiële kriteria waarvolgens seleksieprosedures geëvalueer moet word, billikheid en doeltreffendheid is. Sou die menslikehulpbronfunksie uitgedaag word om sy seleksieprosedure te verdedig, sal dit met geloofwaardige bewyse voor 'n dag moet kan kom om die regverdigheid en doeltreffendheid van die intervensie onder bespreking deur middel van logiese argumente te regverdig. Die probleem is egter dat die meeste seleksieprosedures wat in Suid Afrika gebruik word, waarskynlik nie aan hierdie vereiste sal kan voldoen nie. Die soeke na regverdige en doeltreffende seleksieprosedures noodsaak dus dat die behoefte aan psigometriese oudits aangespreek word vir die terugvoer wat nodig is om die seleksieprosedures meer doeltreffend en regverdig te maak. Dit sal ook terselfdertyd die bewyse verskaf waardeur organisasies hul keuringsprosedures kan regverdig indien teen organisasies opgetree sou word in terme van Suid Afrika se antidiskriminerende arbeidswetgewing.

Die "Guidelines for the Validation and Use of Selection Procedures" wat deur die Vereniging vir Bedryfsielkunde (1998) ontwikkel is, is 'n poging om die ideale proses waarvolgens seleksieprosedures ontwikkel en gevalideer behoort te word, te illustreer. Op voorwaarde dat hierdie Riglyne (1998) aanvaar word as die mees regverdigbare metodologie wat betref die ontwikkeling en regverdiging van seleksieprosedures, word dit noodsaaklik dat organisasies hulle seleksieprosedures en die ontwikkelingsgeskiedenis daarvan van tyd tot tyd evalueer (d.i. 'n periodieke psigometriese oudit) ten einde vas te stel of die menslikehulpbronfunksie die volgende oortuigend kan demonstreer:

- die noodsaaklikheid van die seleksieprosedure uit 'n besigheidsoogpunt;
- die geldigheid van die prestasieteorie waarop die seleksieprosedure gebaseer is; en
- dat die seleksiestrategie die inligting van die aansoeker regverdig kombineer.

’n Kontrolelys is ontwikkel uit relevante psigometriese bronne sodat die psigometriese oudit ’n gestruktureerde lys van aktiwiteite bevat wat die gebruik van ’n seleksieprosedure sal kan regverdig. ’n Psigometriese oudit is gedoen op ’n seleksieprosedure vir die inbelpersoneel van ’n groot Suid Afrikaanse versekeringsfirma. Die oudit het ’n aantal gebreke in hierdie seleksieprosedure en sy ontwikkelingsgeskiedenis uitgewys.

Die prestasiehipotese waarop die keuse van operasionele voorspellers gegrond is, was nie met voldoende helderheid ontwikkel, beredeneer of gedokumenteer om ’n onomwonde aanduiding te gee van die nomologiese netwerk van prestasiedeterminante en prestasiekonstrukte nie. Die eksterne geldigheid van die valideringsontwerp was ook problematies. Geen betroubaarheids-, geldigheids-, billikheids- of nutanalises is ten tyde van die oudit uitgevoer nie.

’n Daaropvolgende korrelasie-analise dui op lae, statisties onbeduidende korrelasies tussen die meerderheid van die gekose voorspellers en die ontwikkelde kriteria. Daar is desnieteenstaande lineêre kombinasies van voorspellers gevind vir elk van die drie inbelsentrumposte wat beduidend matige proporsies kriteriumvariansie verklaar. Die billikheid van die gebruik van die CSR meervoudige regressievergelyking vir wit en swart aansoekers is ondersoek en aanvaarbaar gevind. As gevolg van praktiese beperkinge is die nut van die seleksieprosedure nie geëvalueer nie.

Daar word aanbeveel dat die huidige seleksieprosedure weer noukeurig deur die maatskappy ondersoek sal word om positiewe veranderinge aan die prestasiehipotese en die operasionele kriteriumtellings aan te bring. Daarna moet konkrete bewyse uit betroubaar gegenereerde, metodologiese navorsing weereens verkry word om die relevansie, betroubaarheid en betekenisvolheid van die afleidings wat gemaak is op grond van voorspellerevaluerings te verifieer, om op dié manier moontlike regsgedinge te beperk, indien nie uit te skakel nie.

All truly wise thoughts have been thought already thousands of times; but to make them truly ours we must think them over again honestly; till they take root in our personal experience.

- Goethe

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CHAPTER I

INTRODUCTION AND OBJECTIVE OF THE STUDY

1.1 INTRODUCTION

Organisations have come to exist for a definite reason and a specific purpose, their goal traditionally being to serve their own (beneficial) economic interest by essentially aiming at attaining the highest possible production output with the lowest possible production input. Maximising the economic utility of the products and services the company utilises and produces is the pivot of the capitalistic system. Profit maximisation is thus essentially the goal of companies functioning within the capitalistic system.

A wide range of inter-related organisational activities exist, each representing a different function within the organisation aimed at the optimal and maximum utilisation of resources/production factors in order to realise the primary objective of the organisation. The human resource function represents one of these functions. The inclusion of the human resource function in the spectrum of organisational functions can be justified by its contribution to organisational goals. The contribution to organisational goals can be justified in terms of the human resource function having the ability to maximise the economic utility of the products and services the organisation utilises and produces. The importance of the human resource function, essentially, lies in the equitable and fair acquisition and (beneficial long-term) maintenance of a competent workforce - and in its consequent effective and efficient utilisation - in line with organisational goals through the use of human resource interventions.

The purpose of human resource interventions is twofold, namely they are aimed at affecting (a) the quality of employees entering, moving through or out of the organisation (e.g. by use of recruitment and selection), and (b) the quality of employees currently in the organisation (e.g. by use of training and performance appraisals) (Milkovich & Boudreau, 1994).

Human resource selection represents a critical human resource intervention designed to affect the movement of employees into, through and out of the organisation. As such, selection represents a potentially powerful instrument through which the human resource function can add value to the organisation by employing a candidate, i.e. a means of production, in the most appropriate and efficient manner by selecting from the pool of available candidates the most efficient, potentially most successful individual. Selection thus represents a potentially powerful mechanism through which the human resource function can have a positive or negative impact on the financial position of the organisation. Where personnel assessment procedures fail to produce the most efficient, successful candidate, the company's productivity levels and other set goals will be reached with difficulty. This puts additional pressure on other organisational interventions and programmes to succeed.

Selection represents a visible mechanism through which the access to employment opportunities can be regulated by virtue of its ability to discriminate between applicants in terms of attributes relevant to job performance. It thus becomes evident that selection procedures have the ability to impact powerfully on people's lives. The question consequently arises as to whether the discrimination is in fact fair. Special emphasis is thus placed on the selection procedure and it is therefore, more than other human resource interventions, subject to rigorous scrutiny, especially from the perspectives of fairness and affirmative action.

Two criteria thus exist in terms of which selection procedures should be evaluated, namely efficiency and equity (Milkovich & Boudreau, 1994). Efficiency refers to the organisation's ability to obtain maximum output with minimum input, whereas equity refers to the fairness of organisational procedures and consequent outcomes of such procedures (Boudreau, 1991).

The aforementioned two criteria imply two influential stakeholders. Management, which represents the owners and equity holders of the organisation, evaluates selection procedures primarily in terms of their ability to add value to the organisation, whereas organised labour/the state, which represents the employees of the organisation, evaluates the procedure primarily in terms of the fairness of the impact it has on the lives of the workforce. Should the human resource function be challenged to defend its selection procedure to management and organised labour, it should be able to assemble credible evidence to show the efficiency and equity of the disputed intervention by means of a reasoned justification. Current labour legislation, in effect, demands the justification of the selection procedure by the organisation in terms of the aforementioned two criteria, on behalf of especially organised labour.

The use of psychometric tests in South Africa was, until recently, regulated only by the South African Medical and Dental Council (now the Health Professions Council of South Africa) and the

Test Commission of the Republic of South Africa in terms of Act 56 of 1974. This law differs from other more recent legislation in that it merely stipulates who is entitled to administer which category of psychometric assessment instruments. It therefore implies that the valid and professional use of psychometric tests is dependent on the qualifications of test users only. Empirically verifiable, fair decisions concerning individual candidates and their future in the organisation will be ensured as long as properly qualified individuals are responsible for the decisions being made. In the majority of instances, however, this is found not to be the situation. Hence the need for additional legislation.

From the perspective of equity and affirmative action, the selection procedure can be regulated via current legislation and the "Guidelines for the Validation and Use of Assessment Procedures in the Workplace" (Society of Industrial Psychology, 1998). The Bill of Rights (Constitution, 1996) specifies grounds on which equitable selection procedures should not be based so as to protect job applicants, prospective employees or the current workforce. It is clearly stated in the Constitution of the Republic of South Africa (1996, p.8) that:

> The state (no person) may not unfairly discriminate directly or indirectly against anyone on one or more grounds, including race, gender, sex, pregnancy, marital status, ethnic or social origin, colour, sexual orientation, age, disability, religion, conscience, belief, culture, language and birth.

Pivotal to South African labour law has been the advent of the Employment Equity Act (1998), which has as one of its goals compulsory non-discrimination. Apart from stipulating the grounds on which unfair discrimination is prohibited (same as the above with the inclusion of family responsibility, HIV status and political opinion), chapter two (5) of the Employment Equity Act (1998, p.14) additionally comments on the elimination of unfair discrimination:

> Every employer must take steps to promote equal opportunity in the workplace by eliminating unfair discrimination in any employment policy or practice.

Furthermore, chapter two (8) of the Employment Equity Act (1998, p.16) states the following about psychological testing in South Africa:

> Psychological testing and other similar assessments of an employee are prohibited unless the test or assessment being used –

a) has been scientifically shown to be valid and reliable;

b) can be applied fairly to all employees; and
c) it is not biased against any employee or group.

Yet issues such as bias and fairness are often misinterpreted, if not overlooked, and much confusion prevails as to how assessment procedures should be implemented so as to ensure fair decision-making. The Employment Equity Act (1998) itself to some extent seems to suffer from rather serious misconceptions about psychometric testing. Concrete evidence, reliably generated through methodologically sound research, needs to be obtained in order to verify the appropriateness, reliability and meaningfulness of the inferences made from the test scores of assessment instruments, thereby limiting, if not eliminating, possible cases of litigation.

The promulgation of the Promotion of Equality and Prevention of Unfair Discrimination Bill (1999) focuses specifically on the prohibition and elimination of unfair discrimination. Unfair discrimination in the Act (1999, p.6) is defined as:

> … an act or omission, including any condition, requirement, policy, situation, rule or practice, that has, or is likely to have, the direct or indirect effect of unjustly or unfairly causing disadvantages.

With a special emphasis on recruitment and selection, this includes:

> … the failure to identify and take reasonable measures to remove any barriers to the full enjoyment of access to opportunities by persons who were historically denied such opportunities by law or practice (Republic of South Africa, 1999, p.6)

as well as:

> … subscribing to and applying human resource utilisation, development, promotion and retention practices which unjustly disadvantage persons from particular groups or have the effect of perpetuating consequences of past discrimination in employment (RSA, 1999, p.11),

though it is not unfair discrimination to:

> … distinguish, exclude or prefer any person on the basis of an inherent requirement of a job or a situation (RSA, 1999, p.7).

All the aforementioned pieces of legislation in one way or another make provision for a plaintiff to allege discrimination. If a plaintiff makes out a *prima facie* case of unfair discrimination, the onus is on him to establish adverse impact (indirect discrimination) or disparate treatment (direct discrimination). Factors to be taken into account when deciding whether such allegedly unfair, discriminatory behaviour is reasonable and justifiable in the circumstances include the purpose, nature and the extent of the unfair discrimination and the (resultant) disadvantage (Promotion of Equality and Prevention of Unfair Discrimination Bill, 1999).

The above legislation also implies, even though it does not directly refer to, a defendant and thus the possibility exists that those aspects which *prima facie* appear to constitute unfair discrimination might in fact not be unfair discrimination. Adverse impact does not necessarily imply unfair discrimination. This, however, begs the question of how (i.e. in terms of what evidence) the burden of persuasion resting on the defendant could be met. The defendant must demonstrate the non-discriminatory business-relatedness of his actions and decisions by establishing the validity, the fairness and the utility of the criterion-related inferences made from the scores obtained from an assessment instrument. The defendant must, therefore, be able to refute any charges made against him by providing legally permissible, empirical evidence for the employment practice under scrutiny.

The Guidelines (Society of Industrial Psychology, 1998) represents an attempt by Industrial Psychology as an academic discipline to take the lead on issues concerning the validation and use of assessment instruments in the workplace. The Guidelines (Society of Industrial Psychology, 1998) emphasise the significance of the establishment of equity and efficiency in the personnel selection procedure, and throughout they indicate the importance of the following aspects for the human resource function:

- The business necessity of the selection procedure must be established;
- The selection procedure should be based on a scientifically credible performance theory; and
- The manner in which the selection strategy combines the applicant information must be considered fair.

If, as in the USA, it is accepted that (a) the Guidelines (Society of Industrial Psychology, 1998) enunciate the psychometrically most justifiable modus operandi regarding the development and justification of a selection procedure; and (b) the approach used during litigation for the evaluation of selection procedures will become so sophisticated that it will coincide with the views and procedures set out in the Guidelines (Society of Industrial Psychology, 1998), it will become of critical importance that human resource practitioners initiate the evaluation of current selection procedures in terms of the Guidelines (Society of Industrial Psychology, 1998).

The impact of the Guidelines (Society of Industrial Psychology, 1998) on the world of work is, however, dependent on the extent to which they are studied and understood by human resource practitioners and to the extent to which the motivation exists to apply such knowledge practically in the development and justification of selection procedures. It does not seem unreasonable to postulate that human resource practitioners' motivation to comply with the directives of the Guidelines (Society of Industrial Psychology, 1998) in turn depends on the extent to which such compliance is rewarded. Compliance will be rewarded only if it is valued for its contribution to (a) the financial well-being (the "bottom line") of the company, and (b) the outcome of equal employment opportunity litigation.

Pertaining specifically to the practitioner's knowledge of the validation process and concomitant terminology, ideas and concepts, two distinct states of mind are observable: a meticulous concern for the appropriateness of the methodology and underlying motives with which information pertaining to the validation process is assimilated, dissected, integrated and practised; and a perturbing passiveness indicative of the lack of knowledge and comprehension regarding the scientific process of validation.

Admittedly, it is from the perspective of an almost passive acceptance of issues that human resource decisions are made, more often than not. It is the formation and expression of an opinion not based on firm evidence that gives rise to controversial, often incorrect, perceptions of core issues critical to the understanding, and by implication to the practice, of the different facets of the validation process.

Another perturbing issue is the vernacular involved in expressing ideas and formulating concepts concerned with the validation process. These concepts are often expressed at a substantially high level of abstraction. Some of the concepts related to selection and validation are abstract by nature. They are thus difficult to define in operational terms, and therefore difficult to measure. Yet the very nature of the validation process necessitates the quantification of human resource phenomena in order to be scientifically credible. The move toward greater quantification (and less abstractness) will enable practitioners to obtain firm evidence to make verifiable and defensible claims, as well as empirically substantiated refutations.

As a result, practitioners in South Africa will be able to practice with greater precision and purpose, and will be able to develop an ability to reason and converse specifically in the terminology of the validation process, thereby increasing the standard and sophistication of debate among South African practitioners, which will in turn contribute to national and international competitiveness.

However, research in fact has demonstrated (Boolsen, 1994) that the Guidelines (Society of Industrial Psychology, 1998) are neither read nor understood or even applied to the extent the Society of Industrial Psychology had originally hoped for. The findings reported in Boolsen (1994) suggest that the inability of human resource practitioners to value and reward compliance is, indeed, a contributing factor to this unsatisfactory situation. Six years have passed since the Boolsen (1994) survey, and there is still no reason to suspect that the situation has improved significantly during this time. It seems safe to contend that most of the selection procedures currently in use in South Africa have not been developed in accordance with the Guidelines (Society of Industrial Psychology, 1998). Such selection procedures could, however, be challenged at any point in time in terms of equal employment opportunity legislation. Should this happen, it seems unlikely that the organisations would be able to prove convincingly that the selection practices do not discriminate unfairly.

A critical review of the manner in which the selection procedure was originally developed and justified thus seems to be required to generate *post hoc* the evidence needed to successfully meet the EEO challenges. The introduction of the term psychometric audit seems to be appropriate in capturing and conveying the essence of the envisaged process.

In the quest toward equitable and efficient selection procedures, periodic psychometric audits are required in an attempt, firstly, to achieve greater organisational efficiency and to ensure the equitable utilisation of its human resources. Secondly, the psychometric audit is also required as a basic foundation in terms of which an organisation could justify its selection procedure should it be challenged in terms of anti-discriminatory legislation.

The psychometric audit aims at establishing the scientific rationality of the methodology through which the selection procedure was developed and justified. The audit essentially compares the way in which the selection procedure has actually been developed and justified with the ideal procedure derived from the Guidelines (Society of Industrial Psychology, 1998) and existing psychometric literature.

The purpose of periodic psychometric audits is to point out the degree of adherence of the selection procedure to current legislation and the Guidelines (Society of Industrial Psychology, 1998), and therefore to identify substantial and procedural shortcomings in the design and justification of the selection procedure.

Substantial shortcomings simultaneously refer to the shortcomings related to an individual's rights concerning equitable selection as set out in South African legislation as well as the shortcomings related to management's quest for an efficient selection procedure. Substantial shortcomings thus specifically refer to the use of unreliable and invalid (i.e. irrelevant) predictor information, the failure to obtain valid information on influential determinants of work performance, and the combination of predictor information for decision-making in a manner that results in unfair adverse impact or discrimination.

Procedural shortcomings refer to the shortcomings of the mode, method or procedure with which the selection procedure has been empirically justified compared to the set-out, ideal procedure referred to in this document and in the Guidelines (Society of Industrial Psychology, 1998). Should serious shortcomings be identified, psychometric audits should, furthermore, rectify these by altering the procedure and/or performing the requisite psychometric/statistical analyses. The areas pertaining to the development and justification procedures of the selection procedure present the greatest risk of jeopardising the defense of a selection procedure and should therefore be expertly assessed and improved upon if necessary. At the same time, psychometric audits create an awareness of the fallibility and concomitant dangers of unvalidated selection assessment procedures utilised in organisations. If a selection procedure is challenged by anti-discriminatory legislation, results of the psychometric audit is to be used in the vindication of the organisation.

1.2 THE OBJECTIVE OF THE STUDY

The objective of this study is - in the light of the aforementioned introduction and with the relevant psychometric literature with only the Guidelines (Society of Industrial Psychology, 1998) and the relevant labour legislation as a frame of reference - the initiation of a comprehensive psychometric audit of the current personnel selection procedure for the selection of Call Centre staff at a South African insurance company.

A detailed overview of the objective of the comprehensive psychometric audit entails the following:

- To identify substantive and/or procedural shortcomings of the current selection procedure;
- To introduce suggestions regarding the correction of substantial shortcomings;
- To introduce and illustrate/apply suggestions regarding procedural modifications/corrections; and
- To develop an illustrative case study/norm in terms of which other current and future selection procedures can be evaluated.

1.3 CONFIDENTIALITY

All the information obtained by the Author on the composition and the developmental history of the selection procedure under investigation is highly confidential. The extent to which information on the selection procedure has been documented in this thesis has been subject to the Author's discretion. It is thus possible that specific, detailed descriptions of people, circumstances or procedures have had to be limited, if not omitted, to avoid any possible compromise to the competitive position of the company concerned. Furthermore, opinions expressed in this thesis and conclusions arrived at are those of the Author and are not necessarily to be attributed to the company concerned.

CHAPTER II

RESEARCH METHODOLOGY AND STRUCTURAL OUTLINE OF THE THESIS

2.1 RESEARCH METHODOLOGY

Due to the nature of the psychometric audit, with the theoretical derivatives influencing the sequence of the practical execution of the psychometric audit, the structure of the thesis will deviate somewhat from the conventional format.

The Oxford English Dictionary (1989, p.781) describes an audit as follows:

> A judicial hearing of complaints; an official examination of accounts with *verification by reference to witnesses* and vouchers; to make an official systematic examination of (accounts), so as to ascertain their accuracy (italics added).

The above dictionary definition of an audit is reflected and operationalised in the objective of this study. In the light of the above introduction (Chapter I) and the relevant psychometric literature with only the Guidelines (Society of Industrial Psychology, 1998) and the relevant labour legislation as a frame of reference, the objective of this validation study is the initiation of a comprehensive, systematic, psychometric examination of the current personnel selection procedure for the selection of Call Centre staff at a South African insurance company (hereafter "The Company"). A comprehensive psychometric audit entails the:

❖ Identification of substantive and/or procedural shortcomings of the current selection procedure;
❖ Introduction of suggestions regarding the correction of substantial shortcomings;
❖ Introduction of and illustration/application of suggestions regarding procedural modifications/corrections; and
❖ Development of an illustrative case study/norm in terms of which other current and future selection procedures can be evaluated.

A psychometric audit implies the existence of an explicitly described ideal approach to the development and justification of a selection procedure that can serve as a template to guide the examination of the actual procedure used in the development and justification of the Call Centre selection procedure in an attempt to achieve greater organisational efficiency and to ensure the equitable utilisation of its human resources.

A literature study lays the required theoretical foundations for the development of such a template. In the context of this thesis the literature study encapsulates the ideal procedure: a blueprint on which the practical execution of a validation study should be based on, with the Guidelines (Society of Industrial Psychology, 1998) and the relevant labour legislation as a frame of reference.

The core activities required by the ideal approach to the development and validation of a selection procedure is subsequently distilled from the literature study in the form of a checklist. The checklist represents a summary of the theoretical ideal derived through the literature study in terms of which any personnel selection procedure should be validated. The checklist entails the most significant facets of a validation study; it represents facets that are necessary in the validation of existing selection procedures if the validation of a selection procedure is to be executed comprehensively, precisely and fairly.

A step by step comparison of the actual Call Centre selection procedure and its developmental history, and the ideal approach to the development and justification of a selection procedure, constitute the essence of the psychometric audit. The checklist would then be used to summarise the extent to which the actual selection procedure conforms to the ideal procedure set out in the Guidelines (1998). Such a comparison could, at one extreme of a continuum, indicate that the Call Centre selection procedure has been flawlessly developed and justified and that the procedure has no serious substantive deficiencies. Should this outcome occur, the audit would terminate. There would then be no significant substantive or procedural shortcomings to detract from The Company's ability to defend the Call Centre selection procedure in cases of litigation.

At the other end of the continuum such a comparison could, however, uncover serious substantive and procedural shortcomings. The checklist would again be used to summarise the nature and the extent to which the actual Call Centre selection procedure deviates from the ideal procedure. Should this outcome occur, the audit will continue by trying to perform those phases of the ideal procedure that were neglected in the development and justification of the Call Centre selection procedure and/or by trying to rectify substantive deficiencies in the performance hypothesis.

The psychometric audit aims at establishing the scientific rationality of the methodology through which the selection procedure was developed and justified. A psychometric audit thus requires a detailed, systematic description of the actual selection procedure that is to be audited, as well as a detailed, systematic description of the way in which the procedure was developed and justified.

The compilation of the checklist is followed by a detailed, systematic description of the current selection procedure used for the selection of Call Centre staff at the company under consideration. The positions under investigation are described, followed by detailed descriptions of the following aspects, as necessities in a validation study:

- Job analysis;
- Description of predictor variables; and
- Validation sample.

Should statistical analyses be required to improve the credibility of the actual selection procedure, the SAS and SPSS software packages will be used. The nature of any of the analyses that could be required will necessarily have been described in the literature survey of the ideal procedure.

Companies that could possibly have been interested in participating in the proposed psychometric audit were contacted. What was rather disturbing was the fact that the company under investigation was one of the very few companies that was prepared to have their selection procedure audited. The companies that were contacted either reported that they had had specified positions validated and were therefore not interested in having their selection procedure psychometrically audited, or the companies reported that - although they might not have had specified positions validated before - they still simply were not interested in having the positions psychometrically audited, which would allow them to come closer to limiting, if not eliminating, possible cases of litigation.

A few of the contacted companies were interested initially but, upon closer examination of what the psychometric auditing process entails (under conditions of confidentiality and at no financial cost to the company), declined. It is alarming that, under specified conditions of confidentiality and at no financial cost to the company, a company would nevertheless decline what has undoubtedly become a necessary prerequisite in being able to provide statistical, psychometrically justifiable evidence required for the vindication of organisations should they be challenged by South Africa's anti-discriminatory labour legislation.

What distinguished the company under investigation was, specifically, their concern for the validity of the selection instruments used in conjunction with the developed competencies in the selection of Call Centre staff. That is, the emphasis of The Company's concern was in effect put on the fairness of the selection procedure of Call Centre staff in the light of current labour legislation.

At the time of proposing the idea of the psychometric audit to The Company, The Company had employed a second external Consultant to go ahead with an "actual" validation study of the Call Centre position. The Author's psychometric audit has, therefore, proceeded parallel to the study initiated by the second external Consultant.

After permission to proceed with the proposed psychometric audit was obtained, the Author proceeded by contacting various people within The Company who had access to relevant information. Most information was obtained telephonically, although a few meetings were arranged to further discuss and obtain written, detailed information from the various sources concerning the procedure, development and implementation of the current selection procedure. Special arrangements were made, together with the second external Consultant, to discuss the relevant predictor and criterion data obtained by the organisation to be used for the purposes of the study.

2.2 STRUCTURAL OUTLINE OF THE THESIS

From the introduction into the necessity and the rationale behind the psychometric audit in Chapter I, Chapter II represents a description of the research methodology adopted in this specific psychometric audit. A short, chronological description is given of the manner in which the various pieces of information required for the psychometric audit were obtained.

The theoretical foundation of the psychometric audit is outlined in Chapter III. The theoretical foundation entails an integration of the detailed description of the ideal validation procedure as set out in the Guidelines (Society of Industrial Psychology, 1998) and other relevant psychometric literature, with continuous emphasis on the efficiency and equity of selection procedures. The ideal procedure of the validation of a selection procedure is subsequently summarised in the form of a checklist. The checklist represents a theoretical ideal detailing the most important facets of the validation process according to which any personnel assessment procedure should be validated. Its use lies in the fact that it enables one to tick off, as it were, the critical behaviours that have, or have not, been executed in the validation of a selection procedure which would ensure a valid and credible verdict on the relevance, utility and fairness of the selection procedure.

A detailed, systematic description of the developmental history and the composition of the selection procedure under investigation is set out in Chapter IV. The position, the job analysis, the predictor and criterion variables and the validation sample are described.

An evaluation of the existing selection procedure and recommendations for procedural and substantive improvements to the selection procedure and the manner in which it is justified is set out in Chapter V.

Chapter VI is a summary of the evaluation of the Call Centre selection procedure in the form of a completed checklist. The facets of the development and validation process that are in need of attention are thereby indicated.

Chapter VII consists of the research findings obtained from the statistical analyses undertaken to rectify some of the procedural shortcomings identified in Chapter VI.

Chapter VIII provides a summary of the rationale behind the psychometric audit and lists the major shortcomings identified in the selection procedure under consideration.

CHAPTER III

THE RELEVANT PSYCHOMETRIC LITERATURE DETAILING THE IDEAL PROCEDURE FOR THE DEVELOPMENT AND VALIDATION OF A SELECTION PROCEDURE

3.1 THE IMPLICATIONS OF THE UNAVAILABILITY OF CRITERION INFORMATION

In an investigation into the components of a selection procedure, it becomes evident that in selecting applicants the focus can fall predominantly either on the individual about whom decisions are required or on the selection procedure itself. Psychometric tests essentially serve the purpose of providing information for the decision-maker about the individual. In an evaluation of the entire selection process, the focus should therefore fall on the decisions being made rather than solely on the psychometric properties of the test. This does not imply, however, that psychometric properties are irrelevant. On the contrary. To ensure the efficiency and especially equity of the selection/decision-making procedure, special emphasis should fall on the validity of the procedure according to which selection decisions are made.

In focusing on the decision heuristics used by decision-makers, Cronbach and Gleser (1965) have, in an integrative approach toward personnel selection decision-making, identified the following structural components as part of the selection decision-making process:

- An individual about whom a decision, based on limited information, is required;
- Treatments to which the individual is to be assigned to;
- A decision function prescribing the specific treatment contingent on the obtained information about the individual;
- An outcome, contingent on the assignment of the individual to a treatment, described by a set of multi-dimensional criteria; and
- A utility scale through which the outcome is to be evaluated.

There are two perspectives in terms of which selection decision-making can be conceptualised, namely:

- An individual perspective; and
- An institutional perspective.

From an institutional perspective, the decision-maker is confronted with the challenge to select, on the basis of limited yet relevant information, a sub-group of applicants conditional on the stipulated quota, to maximise the value of the outcome evaluated in terms of a utility scale calibrated in terms of appropriate units.

To maximise the organisational objective of continuous increments in utility, the organisation primarily selects in terms of institutional criteria. Institutional criteria refer to the various facets of work success. To base selection decisions directly on institutional criteria is, however, practically not possible as the information on the criterion, work success, is not available at the time of selection decision-making. Yet the actual outcome (i.e. the ultimate criterion, work success) is the focus of interest in selection decisions.

Cronbach and Gleser (1965, p.22) relevantly observe that this decision-making problem would "enormously be simplified if the decision-maker could anticipate, with complete certainty, the actual outcome for each person under each treatment." As the actual outcome is not available at the time the selection decision is made, the only alternative to random decision-making would therefore be to base the selection decision on selection assessments hypothesised to be related to the criteria of interest, thus enabling the prediction of the expected actual outcome from limited yet relevant applicant information available at the time of selection. The construction of a substitute variable is thus called for (Ghiselli, Campbell & Zedeck, 1981).

The only available information that could possibly serve as a substitute at the time the selection decision is made would be biographical, physical, psychological and behavioural information on the applicant. Such information can be considered relevant substitute information to the extent to which it yields usefulness in the decision-making process and the extent to which it permits an accurate estimate of the final criterion. An accurate estimate of the final criterion will be possible from the substitute information to the degree to which the substitute systematically correlates with a measure of the ultimate criterion (Guion, 1965). Two options only exist in terms of which an acceptable and appropriate substitute for the criterion can be found:

- ❖ The first option requires the operationalisation of requisite, critical person-centred constructs, inferred from a systematic job analysis, believed to be determinants of criterion performance;
- ❖ In terms of the second option a simulation of the demands, inferred from a systematic job analysis, that collectively constitute the job in question, is required.

Both options obtain substitute criterion information through behaviour elicited by a stimulus set. In the first case, the stimuli are designed so that the testee's response to them is primarily a function of a specific, defined construct, whereas in the second case the stimuli are designed to elicit the same response as actual facets of the job would have elicited. Although the reaction to the stimulus set is again determined by a construct(s), the underlying performance determinants are not necessarily known.

Options one and two, furthermore, require empirical proof in establishing the relevance of the substitute as an estimate of the ultimate criterion. It must thus be established that the substitute, inferred from the ultimate criterion, is indeed systematically correlated with work success. The nature of the evidence required for empirical proof, however, differs across the two options:

In terms of option one it must be empirically established that construct-valid measures of the presumed critical constructs statistically significantly explain variance in a construct-valid measure of the ultimate criterion.

In terms of option two, to attain actual facets of the job, a job content domain (Guion, 1991) must be defined clearly and incisively for the full range of performance lying within that domain. It then should be possible to sample tasks in such a way that the complete domain is adequately represented and inferences about the complete domain are a reasonable possibility (Thorndike, 1982). Hence it must be established whether a (factorially) content-valid description of the performance domain is obtained via a simulation, and whether the job domain description statistically significantly correlates with a construct-valid measure of the ultimate criterion.

The most prominent differences between the two options lies in the underlying logic in terms of which substitute measures are generated. Whereas option two can proceed without much significant understanding of why inter-individual differences exist, option one requires the explication of a performance theory. The underlying argument of both options, however, maintains that fair and effective selection is contingent on the identification of appropriate substitutes for the ultimate criterion.

The extent to which effective substitute criterion measures are obtained should be the subject of empirical validation studies. Such a comprehensive investigation, in which substitutes for the ultimate criterion are developed, functions as a basis on which the entire selection procedure can be justified empirically. Such a justification proceeds in terms of the two substantial criteria of the validation process, namely through the golden threads of equity and efficiency.

3.2 JOB ANALYSIS AND THEORISING

The question as to why there are differences in job performance, as a precursor to the questions of whom and how to select, provides the impetus for an investigation into the resolution of the challenge introduced by the unavailability of criterion information. The question as to the existence of differences in job performance necessitates the explication of an underlying tentative performance theory.

It is from such a scientific and hypothesis-testing perspective that the validity of a selection procedure should be viewed. Landy (1986, p.1187-1188) clarifies any conceptual misconceptions that might exist about the primary foundation on which the validation investigation is based by stating that:

> The validity analyst is carrying out traditional hypothesis testing. At least by implication, the hypothesis to be considered is of the following form: People who do well on test X will do well on activity Y, or Y =f(X). Investigators should not lose sight of the fact that validity studies are attempts to develop a theory of performance that explains how an individual can (or will) meet the demands of a particular job.

Guion (1991, p.335) supports the above by stating that:

> Hypothesis development should proceed rationally toward the development of a working theory.

Two aspects regarding valid theoretical explanations should be considered, namely:

- Valid theoretical explanations of the different dimensions of work behaviour are necessary, though not sufficient, conditions for efficient and equitable human resource interventions; and
- The validity of the theoretical explanations for the different dimensions of work behaviour depend on the quality and thoroughness of the theorising. The importance of theorising lies in the fact that it produces theoretical explanations in response to the question that initiated the research.

The task of the practitioner is thus to formulate sound hypotheses about relationships between predictor constructs and the criterion construct (Society for Industrial Psychology, 1998). Informed hypothesis-making requires an understanding of the job, in its components and as a whole, for which applicants are to be hired (Guion, 1991). To be able to predict institutional criteria (dimensions of work success), however, measures correlating with performance are desired, in other words measures of critical attributes that determine success are desired. These critical variables can be identified via a job analysis.

Collecting information describing verifiable job behaviour(s) and activities, i.e. undertaking a comprehensive, systematic job analysis so as to identify the components of a job, should provide the researcher with sufficient and appropriate information for credible and valid judgements about predictor constructs and the conceptualisation of the criterion construct. A thorough job analysis should document the environment in which the work is performed so as to identify specific organisational characteristics and components that are important in determining job success. It should also ascertain the tasks, obligations and responsibilities performed on the job (i.e. job description) from which it is possible to infer the minimum human qualities required by the job incumbent for the successful performance and completion of the task(s) at hand (i.e. job specification).

The job specification is, essentially, a complex hypothesis for the explanation of job performance. Guion (1991, p.335), who in part reiterates Landy's (1986) argument, explains the process of hypothesising as a continuous, integrative approach in selection and validation procedures as follows:

> … the hypothesis developer must imagine, perhaps somewhat introspectively, the nature of the personal demands placed on individual workers by the valued criteria and the worker characteristics needed to meet those demands.

The organisation determines the knowledge, skills, abilities and personal characteristics to match both the content and the context of the job. It should also be pointed out that options one and two, in terms of which correlates of performance can be furnished as mentioned earlier, both require a thorough job analysis and job description for the development of suitable predictors. This enables the identification of the requisite characteristics and relevant job performance incidents for options one and two, respectively.

It is not merely for reasons of theoretical debate or literary accuracy that the job analysis procedure is a functional core mechanism in the achievement of valid and credible research results and fair assessment decisions in the validation process. Although its value is frequently underestimated, the job analysis is indispensable in selection and validation procedures as it enables the conceptualisation of the criterion construct without which prediction would be impossible since, without an understanding of what constitutes success, there would be no way of deriving a tool for its prediction.

Building on McCormick's (1979) definition, Harvey (1991, p.74) comprehensively defines the job analysis procedure as:

> ... the collection of data describing a) observable (or otherwise verifiable) job behaviors performed by workers, including both *what is accomplished* as well as *what technologies are employed* to accomplish the end results and b) verifiable characteristics of the job environment with which workers interact, including physical, mechanical, social, and informational elements.

In a categorisation of the above activities, Lawsche and Balma (1966) define the job analysis procedure in terms of available and obtained information by referring to four types of information which may be collected in a job analysis, namely overall information, trait information, operations information and activity information.

Various discussions on the different types of job analysis methods are available (e.g. Cascio, 1991a; Gerber, Nel & van Dyk, 1998; Harvey, 1991; Muchinsky, 1997; Tiffin & McCormick, 1965). Methods of job analysis can be classified into two main groups: general techniques and specialised techniques. General techniques involve observation, interviewing, questionnaires and incumbent's logbook/diary. Specialised techniques include functional job analysis and the position analysis questionnaire.

3.3 VALIDITY

The crucial consideration in test (score) validation is whether inferences made from test scores are permissible. In the case of personnel selection, the question thus is whether credible inferences can be made regarding expected future criterion performance from actual, available predictor scores. More specifically, test validation refers to the process through which information is acquired and accumulated for the substantiation and support of the inferences made from test scores (Binning & Barrett, 1989; Ellis & Blustein, 1991; Kane, 1992; Landy, 1986).

The validity of inferences made can be determined in a variety of ways. It is, however, the quality of the evidence that is of primary importance. The three types of validity demonstrate the available, most prominent strategies for validation investigations, namely (Binning & Barrett, 1989; Ellis & Blustein, 1991; Kane, 1992; Landy, 1986; Messick, 1975):

- Content-related validity;
- Criterion-related validity; and
- Construct-related validity.

The typical approach to the validation of selection procedures would be to select only one of these three strategies. Eliminating any one of these three strategies from the validation research design would compromise the validity of the research design and would result in the relevance and the quality of the validation investigation being questioned. A lack of empirical support for the claim of equitable and efficient employment practices would, in turn, increase the vulnerability of the organisation in cases of litigation.

Landy (1986) supports the above by referring to the practice of selecting a single strategy as a "stamp collecting approach". Landy (1986, p.1185), supported in his perspective by Binning and Barrett (1989) and Ellis and Blustein (1991), reiterates his unificationist perspective as follows:

> ... the labels *content*, *construct*, and *criterion-related* are not completely useless, nor are they interchangeable. They had their value in 1954, and they have their value in 1986. However, their value is not as types of validity. Instead, their value is in pointing out there is more than one type of inference that can be made from a test score.

Landy (1986, p.1188) further argues that:

> Aspects of validity cannot be easily separated from one another. Because the words *content*, *criterion*, and *construct* can be used as aids in discussion, one should not be seduced into thinking of those words as standing for discrete and independent processes. Instead, the words simply represent parts of a larger system that addresses the goal of hypothesis testing.

Ellis and Blustein (1991, p.551) add that:

> Applying the unificationist view to measurement suggests that constructing a test is a scientific endeavour that attempts to understand or predict human behavior. If tests and measures are operational definitions of theoretical constructs…, then measurement is subject to vigorous application of scientific thought and measures (i.e. traditional hypothesis testing research).

This means that:

> … theory, constructs, and hypotheses (inferences) pertaining to the test must be explicated before any empirical data are collected. Thus, the process of constructing tests and validating the inferences are both theoretically driven and evaluated according to established research design principles and criteria (Ellis & Blustein, 1991, p.554).

From the perspective of validation research, the validity and credibility of statements on the validity of the performance hypothesis derived from the job description depend fundamentally on the scientific rationality of the argument through which the conclusions were derived. The validity of the performance hypothesis will determine the ability to answer questions related to why differences in job performance exist, and will determine the (in)ability to differentiate between better and poorer employment prospects. Ineffective selection impacts on "the bottom line" and people's lives, and hence the need to evaluate the selection procedure in terms of equity and efficiency. This has important implications for the type of evidence that is to be generated, and the manner in which it should be generated should the human resource function be called upon to defend its selection procedures in terms of equity and efficiency.

3.4 OPERATIONALISATION

The research question as to why differences in job performance exist leads to a systematic and thorough job analysis from which a job description is compiled. With the information obtained from the job description, the ultimate criterion can be conceptualised in terms of its primary dimensions. Through the creative process of theorising, a performance hypothesis is derived. The tentative performance theory is subsequently reformulated as a research problem. Using conventional LISREL notation (Jöreskog & Sörbom, 1993), the research question can be written as follows:

$$\text{Is } \eta = f[\xi_i];\ i = 1, 2, 3, \ldots p?$$

where η = work performance construct; and

ξ = assumed critical person attributes derived from the job description.

In establishing clearly and confidently the different relations as part of the formulation of the research problem, the clarity and unambiguousness of the stated problem becomes essential. The characteristics of clarity and unambiguousness and the ability to imply possibilities of empirical testing are three determinants of effective problem statements (Kerlinger, 1986).

In reaction to the original research question, the research hypothesis is formulated as a statement regarding the nature of the relations between the constructs of the research problem, where η is the criterion construct to be predicted and ξ the construct that is used to explain variance/differences in work success. In LISREL (Jöreskog & Sörbom, 1993) notation thus:

$$\eta = f[\xi_i];\ i = 1, 2, 3, \ldots p$$

To develop a rational hypothesis, the criterion and predictor constructs must be defined carefully. Furthermore, apart from having to reflect the nature of the relations between variables, hypotheses, as conjectural statements, are evaluated in terms of two additional criteria:

- Hypotheses must carry clear implications for the testing of stated relations; and
- Hypotheses must carry clear implications for the measurement of the constructs comprising the hypothesis (Kerlinger, 1986).

These properties that are desired in a theory, aspire to one and the same thing: they represent the ultimate goal of hypotheses construction, namely the aspiration toward a higher degree of empirical content or testability (Popper, 1963).

It is, however, neither viable nor even possible to test the research hypothesis directly as it stands ($\eta = f[\xi]$), as it is formulated in terms of abstract concepts which are not directly measurable. The tentative performance theory, the research problem and the substantive research hypothesis are constructed from constructs or latent variables. To be empirically testable, the research hypothesis should be formulated in terms of directly measurable entities. The hypothesis should thus be operationalised.

Without operationalisation, measurement would be impossible and the quest for quantification would be to no avail. The importance of successful operationalisation lies in the methodology of the study which serves the epistemological ideal of arriving at a valid and credible verdict on the validity of the research hypothesis.

A construct is an "in the head variable", an intellectual construction of the mind, a cognitive building block without which a person would not be able to process thoughts and generate ideas on existing phenomena in Nature. In the nomological network, the (structural) universe in which constructs exist and relate to one another, constructs comprise the most basic structural components.

Conceptualisation and operationalisation represent two mutually complementary processes through which the meaning of constructs can be explicated (Mouton and Marais, 1990). Two dimensions of meaning can be distinguished:

- A connotative dimension; and
- A denotative dimension.

The connotative dimension refers to the internal structure of an intellectual idea. The connotative meaning of a construct is conceptualised through a literary definition of the abstract idea that the construct represents. The conceptualisation of a construct could be considered theoretically valid if:

- All the dimensions of meaning, implied by the way in which the construct is used, are identified; and
- The dimensions of meaning are mutually exclusive.

The denotative meaning, on the other hand, is explicated through the process of operationalisation, whereby an operational definition is established to define the observable manifestations of the construct, thereby obtaining an empirical grasp on the construct. Two types of operational definitions can be distinguished:

- Experimental operational definition; and
- Measured operational definition.

The first operational definition specifies the actions required for the manipulation of the construct to different levels or conditions. The second, more prevalent type of operational definition determines the actions required to elicit the behaviour through which the construct manifests itself. The measured operational definition can be proposed as a solution to the problem of the non-measurable, abstract nature of constructs in that, as Stevens (1946, p.677) suggests, "measurement is the assignment of numerals to an indicant of a property of an individual according to certain rules."

It is thus implied that the property of an individual is being measured rather than the individual as such. In an explantion of Steven's (1946) definition, Kerlinger (1986) points out the relevance of the definition to the behavioural sciences. Measurement is possible because and to the degree that there exists a correspondence between the characteristics of numerals and the characteristics of the attributes to be measured. Thus, measurement is possible due to the degree of isomorphism evident between the numerals and the attributes to be measured. The numerical system can thus be used as a model (a simplified "as if" representation of a phenomenon) through which the attribute to be measured can be described and replaced.

Measurement occurs indirectly via a behavioural indicant (Gatewood & Feild, 1994). It is thus implied that a psychological measuring instrument elicits a sample of behaviour in which the underlying construct of interest systematically manifests itself via the application of a standardised sample of stimuli to an individual, in which any elicited reaction would in part be a function of the construct of interest. A psychological measuring instrument is thus nothing more than an objective, standardised sample of stimuli through which the underlying construct of interest is expressed in terms of observable behaviour. More specifically, Owen and Taljaard (1989, p.446) define psychological tests as:

> ... evaluation and assessment procedures that have the specific purpose of determining people's characteristics in the field of mental ability, aptitude, interest, personality composition and personality functioning. They comprise a collection of tasks or questions or items that are aimed at eliciting a specific type of behaviour under standard circumstances, on the basis of which scores with acceptable psychometric characteristics such as satisfactory validity and reliability coefficients can be deduced according to prescribed procedures.

The behavioural response to the stimulus sample is contingent on the construct of interest and any inter- and intra-individual variance in the obtained score should ideally reflect differences in the construct of interest only. Therefore, the behavioural responses elicited through the stimulus sample should be contingent on all the facets of the construct of interest only, and any variance obtained in the observed scores should be a reflection of the variance in the various facets of the construct of interest only. However, the quest for a comprehensive and pure measurement is, realistically, never completely attainable. Numerous extraneous influences produce variance in the observed score over and above that produced by the construct of interest. The behavioural response to the stimulus sample is thus not solely a function of the construct to be measured, but also a function of other stable and systematic yet irrelevant as well as unstable (unknown) attributes. In addition, though less of a problem, there is always the possibility of constructing a stimulus sample that does not contain behavioural stimuli to cover all the facets of the construct.

Variance existing in the predictor and criterion measures of interest will thus reflect the effect of measurement contamination (the proportion of irrelevant variance in the measures and the presence of other stable and systematic yet irrelevant attributes as well as an array of unknown, unstable attributes which, when combined, exhibit a random-like character), measurement deficiency (the proportion of unexplained, systematic variance in the predictor and criterion constructs) and measurement relevance (the extent to which predictor and criterion measures overlap with their respective constructs). The concepts of measurement contamination, relevance and deficiency in the operational X and Y measures should be assessed by examining the reliability and construct validity of the operational measures.

Obtained measures will contain measurement error. Two types of measurement error can be distinguished, namely systematic and random error (Guion, 1965). The identification of systematic measurement error arising from irrelevant attributes of the testee is important in that it produces irrelevant inter-individual differences observed as systematic variance in the observed score. Random measurement error, arising from the measurement instrument or attributes of the testee, however, produces inter- and intra-individual variance. Any extraneous influence, i.e. influence not relevant to the purpose of measurement, creates ambiguity in the observed score.

The above comments clearly suggest that the control of both types of measurement error is required to achieve the theoretical ideal that differences in obtained test performance should solely be due to differences in the total construct to be measured. It is thus the goal to remove any irrelevant latent variables or to keep them constant so as to attempt to achieve the ideal that variance in the obtained scores can solely be interpreted in terms of the construct to be measured and not in terms of irrelevant latent variables. Item analysis and standardisation are two processes designed either to remove irrelevant latent variables or to keep them constant so as to minimise, if not eliminate, the effect of extraneous variance in observed scores, and to control stimuli by attempting to keep variables constant over different users, places and times.

The substantive research hypothesis is made empirically verifiable through the process of operationalisation by which observable/testable implications are derived from the substantive research hypothesis via a deductive argument. The deductive argument involves the identification of predictors as a substitute for the critical person characteristics, and the intermediate criterion as a substitute for the final criterion, work success. The deductive argument has the following basic structure:

Statement: η is a function of ξ_i(theoretical research hypothesis);

Premise I: Y is a (reliable and construct-valid) measure of η (operational definition of η construct);

Premise II: X_i are (reliable and construct-valid) measures of ξ_i (operational definition of ξ_i construct);

Conclusion: Y is a function of X_i (operational research hypothesis).

The validity and credibility of the (implicit) claim that the operational hypothesis can be tested as a substitute for the substantive research hypothesis is dependent on the validity of the deductive argument, which in turn is dependent on the validity of the operational definitions contained in the argument.

Comprehensive, pure and uncontaminated measurement is emphasised throughout the measurement process. The importance of comprehensive, pure and uncontaminated measurement lies therein, that the validity of the premises in the deductive argument is determined by the extent to which the construct, as constitutively defined, is comprehensively and purely measured. Without successful operationalisation, thus, validation would be impossible and the quest for the justification of the selection procedure to no avail. The importance of successful operationalisation lies in the methodology of the study which serves the epistemological ideal of arriving at a valid and credible verdict on the validity of the research hypothesis.

3.5 CRITERION MEASUREMENT

In the observation, documentation and evaluation of on-the-job behaviour, the degree of success attained by the individual in reaching organisational objectives is evaluated. Such an evaluation is achieved via a performance appraisal procedure – a systematic description of the strengths and weaknesses within and between individual employees or groups of employees (Cascio, 1991a) involving two distinct processes: observation and judgement. Objective (e.g. production data; personnel data) and subjective (e.g. human judgement) measures of performance can be obtained.

The goal of performance appraisal, essentially, is to make distinctions especially among people in the same job. Performance standards provide the critical link in the process. Performance standards are essential as their absence often results in unequal treatment and unfair discrimination. Ultimately, it is management's responsibility to establish levels of performance deemed acceptable and unacceptable for each of the relevant and critical areas of performance identified.

The goal thus becomes to obtain "an approximate estimate of (the) ultimate criterion by selecting one or more actual (appropriate) criteria" (Blum & Naylor, 1968, p.176). The primary purpose of the intermediate/substitute criterion is that it should "measure the contribution of the individual to the overall efficiency of the organization" (Brodgen & Taylor, 1950, p.139) for which, for a given activity, it is "an index by which (one) can measure the degree of success achieved by various individuals" (Nagle, 1953, p.272). The fact that a substitute has been developed and applied does not, however, make the substitute omnipotent. The fallibility of the substitute lies in the degree to which it fails to accurately measure the individual's contribution due to measurement error as previously discussed.

From the above, thus, the aim derives to identify the success components (criteria) of the job that function as yardsticks for success measures, so as to employ individuals whose predicted performance most closely approximates success as defined. Criteria, therefore, have to be developed. Identifying such elementary units of performance is the first step in criterion development (Landy, 1989).

Blum and Naylor (1968) listed 14 requirements for criteria - or as Weitz (in Blum & Naylor, 1968, p.182)) so aptly remarks "criteria for criteria" - which refer to characteristics necessary and/or desirable in any criterion. In combining the criteria listed by Blum and Naylor (1968) and Muchinsky, Kriek and Schreuder (1998), the Author has identified the following criteria (in no specific order) for criterion development:

- *Relevance and representativeness*: criteria should be relevant and representative of the job as identified via a thorough job analysis;
- *Situational consistency*: criteria must endure over time and across situations reliably;
- *Measurability*: criteria must neither be too expensive nor too hard to measure; and
- *Contamination and bias free*: the proportion of irrelevant, intermediate criterion variance should be kept to a minimum (i.e. minimal criterion contamination) so as to minimise differences of results possibly caused by factors unrelated to the construct of interest.

The above requirements should not, however, override the importance of other identified requirements for criterion development, but rather all should be considered in the selection of criterion measures. Factors which should be considered in the development of a criterion, moreover, are the degree to which the actual criterion underrepresents the ultimate criterion (criterion deficiency); the degree to which the actual criterion overlaps with the ultimate criterion (criterion relevance); and any variance in the actual criterion unrelated to the ultimate criterion (criterion contamination) subdivided into random (unreliable) and systematic error variance (bias).

Desirable steps to effective criterion development have been outlined specifically by Guion (1961) and Nagle (1953). Various performance appraisal techniques exist that could be used to obtain criterion measures. Operational criterion measures are best obtained via performance appraisal techniques such as the Behavioural Observation Scale (BOS) or the Behaviourally Anchored Rating Scales (BARS) that permit the use of more sophisticated statistical analyses (e.g. item analysis, factor analysis, LISREL) in their psychometric evaluation. A very broad overview of the desired sequence of the development of an operational criterion measure looks as follows (Cascio, 1991a; Guion, 1965; Nagle, 1953):

- *Conduct a job analysis*: a thorough job analysis should be conducted using the critical incident technique in a description of incidents describing competent, average, and incompetent job performance;
- *Cluster the critical incidents into behavioural items*: Similar/identical incidents are grouped together as one behavioural item/statement;
- *Cluster behavioural items into criteria (BOS) or into performance criteria (BARS)*: Behavioural items with a common theme are clustered together to form a performance area; and
- *Assess inter-judge agreement*: Relocate items to BOS criteria or performance criteria (BARS).

Continuing the development of the operational criterion measure by use of the BOS method, the following steps of assessing the construct validity, constructing the measuring instrument, and the process of item analysis and reliability and factorial validity analysis have to be completed. For the completion of the BARS method the assignment of values to behavioural items and the formation of the rating scales are needed.

Discussions on the types and the development of criteria are comprehensive and abundant (Blum & Naylor, 1986; Guion, 1991; Muchinsky, 1997; Nagle, 1953). The significant role criteria hold in the selection process, as well as the importance of the job analysis procedure throughout the selection and validation procedure, is summarised by the Uniform Guidelines (1978, p.38300-38301) as follows:

> Whatever criteria are used should represent important or crucial work behavior(s) or work outcomes.... The bases for selection of the criterion measures should be provided, together with references of the

> evidence considered in making the selection of criterion measures. A full description of all criteria on which (the) data were collected and means by which they were observed, recorded, evaluated, and quantified should be provided. If rating techniques are used as criterion measures, the appraisal form(s) and instructions to the raters should be explicitly described and available. All steps taken to ensure that criterion measures are free from factors which would unfairly alter the scores of members of any group should be described.

If the final criterion, job success, is a multi-dimensional construct, it must be defined theoretically as such and subsequently operationalised in terms of behavioural indices that will reflect each of the construct dimensions so as to ensure a pure and comprehensive measure of the final criterion. Toops (in Austin and Villanova, 1992) observes that even in simple jobs success is multi-dimensional.

Hence the utilisation of a single, intermediate criterion for the operationalisation of the (multi-dimensional) final criterion will necessarily lead to substantial criterion deficiency (Blum & Naylor, 1968). It thus follows that the intermediate criterion should also be multi-dimensional in order to represent a valid measure of the final criterion. Two types of multi-dimensional, intermediate criteria are typically distinguished:

- ❖ A composite criterion as a weighted, usually linear combination of single criteria, each representing a dimension of the final criterion, work success; and
- ❖ A multiple criterion as a multi-dimensional criterion space in which each dimension in the space represents a dimension of the final criterion.

The crucial point that needs to be clarified after performance information on the various performance facets via measurement has been obtained is, consequently, the question of the combination of data, i.e. whether the various obtained criterion measures should be combined into a composite or whether each criterion measure should be treated separately.

The strongest advocates of the composite criterion (Brogden & Taylor, 1950; Nagle, 1953; Thorndike, 1949) contend that the criterion should provide a yardstick of "success" (Nagle, 1953, p.272) or "value to the organisation" (Brogden & Taylor, 1950) of each individual. Such a single index is indispensable in decision-making and individual comparisons. The above authors thus contend that even if criterion dimensions are treated separately in validation investigations, they should be combined into a composite when a decision on an individual is required. Quantitative weighting schemes, which rank each criterion in terms of its importance, allow the criterion elements to be weighted objectively.

Toops (in Austin & Villanova, 1992, p.846) clarifies the dilemma concerning the combination of criterion measures into a unitary score:

> The success, then, of an individual, about which we prate so glibly, is a complex thing, and if it is to be made, artificially, into a unitary variable one must be compounded of the weighted sum of the several component parts, as one, simplest, conception of the matter.

The advocates of multiple criteria contend that different variable measures should not be combined, their reasons being analogous to Cattell's (1957, p.11) point of view that "(t)en men and two bottles of beer cannot be added to give the same total as two men and ten bottles of beer." Combining the measures thus leads to ambiguity and the non-sensicality of the composite. Dunnette (1963) seems to simplify the dilemma by stating that high intercorrelations represent the justification for the combination into a composite criterion, whereas low correlations justify the use of multiple criteria. As Thorndike (1949, p.149) explains:

> In general, high correlation between different intermediate criterion measures strengthens the rational basis for accepting any one of them as a useful criterion, since each of them receives some support from the rational justification of the other. Lack of correlation weakens faith in one or both measures, except in so far as each measures distinct aspects of performance for which there is no rational basis to expect intercorrelations.

Schmidt and Kaplan (1971) later remarked that combining various criterion dimensions into a composite implies the existence of a single underlying dimension in job performance, but it does not imply that the single underlying dimension is by nature psychological or behavioural. Brodgen and Taylor (1950), amongst others, focus on utility analyses as one of the core procedures of selection procedures; they point out that when the criteria are all relevant measures of economic variables (i.e. criteria converted into a monetary value) they can be combined into a composite regardless of their intercorrelations. Schmidt and Kaplan (1971) further argue that predictor validity can be higher for a factorially complex criterion than for a factorially unitary criterion. Thus, increases in heterogeneity in the criterion can lead to increased validity with a factorially complex predictor. The importance of the quality and relevance of the criterion in validation investigations cannot be evaded; continuous emphasis on its significance throughout the selection and validation procedures is essential.

The resolution of the composite/multiple criterion dilemma fundamentally depends on the research objectives. The aforementioned two methods are legitimate for their own purposes: if managerial decision-making is the objective, the criterion measures should be weighted (regardless of their intercorrelations) into a composite representing an economic construct of the overall value to the organisation. On the other hand, criterion elements are best kept separate if an understanding of the criterion-predictor relationship is required for the achievement of psychological goals (Schmidt and Kaplan, 1971).

With the knowledge of appropriate criteria and what constitutes success, the choice of predictors becomes a challenge. In considering predictor constructs, it should be evident that work behaviour is complex and cannot optimally be predicted equally for all. Its complexity is, furthermore, evident in that work behaviour is only in part a function of the characteristics of the individual and for the rest it is a function of other situational/contextual variables. It is thus implied that multiple predictors, situational and personal variables as predictors, and possible moderators (a third variable influencing the predictor-criterion correlation) should be of concern in the choice of the predictor (Guion, 1991).

3.6 CHOICE OF PREDICTORS

Given the development of relevant criteria, the identification and/or development of appropriate measuring instruments is the next step to follow in the process of operationalisation. On the basis of the presumed critical latent variables identified from the job description as a substitute for the institutional criteria, appropriate measuring instruments must be identified for the measurement of the presumed critical characteristics. Procedures such as interviews, references, application forms, assessment centres and psychometric tests should be considered as measuring instruments for the critical person variables. The choice of measurement techniques should be made in terms of the efficiency (i.e. the reliability, validity, cost and utility) of the technique for the measurement of the specific attribute.

Construct validity refers to the extent to which a measuring instrument measures the construct it was designed to measure in accordance with its constitutive definition (a deductive perspective on construct validity). A construct as an intellectual idea has a specific internal structure and is embedded in a large nomological network of constructs. Both the internal structure and the nomological network of constructs should be reflected in the constitutive definition of the construct. This is true not only for predictor constructs, but also for the criterion construct.

Construct validity, furthermore, refers to the extent to which theoretical/connotative meaning can be attached to the scores obtained from a measuring instrument (an inductive perspective on construct validity).

The validity and the credibility of the claim that the operational hypothesis can be tested as a substitute for the substantive performance hypothesis is dependent on the validity of the deductive argument in terms of which the substitute performance hypothesis is operationalised. This, in turn, is dependent on the validity of the operational definitions contained in the argument. It thus becomes critical to be able to justify the choice of predictors in terms of reliability and construct validity.

Construct validation should be understood in terms of two dimensions, namely the focus of the analysis (whether internal or external) and the orientation underlying the analysis (whether deductive/confirmatory or inductive/exploratory). Construct validation could, therefore, either refer to a process which seeks empirical confirmation for the theoretical directives emanating from the constitutive definition on the relationships between the relevant construct and other constructs contained in the nomological network through correlation and regression analyses; or it can refer to a process which examines the internal factor structure through (confirmatory) factor analysis. In the ideal case, both these dimensions should be addressed.

Theoretical/connotative meaning could be sought for scores obtained from the measuring instrument by inferring such meaning from the correlations and regression relationships observed between measures obtained on the instrument concerned and measures obtained on other constructs, as well as from the internal factor structure of the instrument derived through (exploratory) factor analysis. Such an inductive approach is, however, not recommended in validation research. It would not be consistent with Landy's (1986) conceptualisation of selection validation research as hypothesis testing. Factor analysis plays an important role in both confirmatory and explanatory approaches to construct validation with an internal focus. Structural equation modeling through for example the LISREL technique (Jöreskog & Sörbom, 1993) is the recommended procedure for confirmatory factor analysis.

The validity of operationalised constructs is ensured to the degree to which they comply with the demands of content and construct validity (that is, to the degree to which it is possible to make inferences from the operational measures about the construct of interest. Three threats to construct validity resulting in operational deficiency and operational contamination have been identified by Cook and Campbell (1979):

- The inadequate preoperational explication of constructs;
- Operational deficiency and contamination resulting from single exemplar research measurements (where construct have not been operationalised to incorporate a variety of meaning dimensions); and
- Operational deficiency and contamination arising from the utilisation of single-method data collection techniques.

3.7 VALIDATION AND SAMPLING

The research/validation design refers to the plan, structure and strategy of the validation investigation (Kerlinger, 1986). In validation research the research design, narrowly interpreted, refers to the theoretical strategy, captured in a schematic representation, on the way to investigate the validity of the operational hypothesis. Or it can be interpreted more broadly as the total theoretical strategy on the way to investigate the validity of the substantive research hypothesis.

The validity of selection procedures can be examined through various validation designs. Tiffin (1946) appears to have been the first to distinguish between two broad methods of validation, namely concurrent and predictive validation research designs (Barrett, Philips & Alexander, 1981). Guion and Cranny (1982) and Sussmann and Robertson (1986), however, argue that the simple dichotomous distinction proposed by Tiffen (1946) does not provide a satisfactorily comprehensive coverage of the different, possible validation research designs. Incorporating the proposals of Tiffen (1946) and Guion and Cranny (1982), Sussmann and Robertson (1986) have proposed a nonexhaustive list of eleven different validation designs (Table 3.1) of which designs 1 to 9 are the most prominent.

Table 3.1 Eleven validation research design variations as a function of timing of test and performance measurement and nature of selection decisions

Design	Before employment	Selection decision	At entry	After short tenure	After extended tenure
1.	X	R	-	-	P
2.	-	R	X	-	P
3.	X	E	-	-	P
4.	-	E	X	-	P
5.	X	X	-	-	P
6.	-	R	-	X, P	-
7.	-	R	-	-	X, P
8.	-	E	-	X, P	-
9.	-	E	-	-	X, P
10.	-	E	-	-	X, P (CS)
11.	-	E	-	-	A, P

Note: E=existing test(s); X=experimental test(s); P=job performance measures; R=random selection; A=archival data; CS=cross-sectional, present employees

(Sussmann & Robertson, 1986, p.462)

The two broad validation designs, predictive and concurrent validation designs, are logically tied to two types of validity, namely predictive and concurrent validity. The former refers to a demonstrated relationship between test scores of applicants and some future behaviour on the job, while the latter refers to a demonstration of a relationship between job performance and scores on a performance assessment instrument obtained at approximately the same time. The most important distinction between predictive validity designs and concurrent designs is the element of time, where individual scores are obtained at one point and criterion scores are obtained at a later stage or are obtained simultaneously. Designs 1 to 5 represent predictive designs because of the non-trivial time lapse involved in the collection of predictor data (X) and the job performance measures (P). Designs 6 to 11, in contrast, represent concurrent designs due to the predictor and job performance measures being obtained simultaneously. The aim of concurrent designs is to estimate present performance on a criterion measure from scores on a predictor.

The first five predictive designs differ in terms of whether the predictor is administered before or after the selection decision is made, and thus also in terms of the way in which the selection decision is made. Randomisation (designs 1 and 2), the use of existing procedures (designs 3 and 4) and experimental predictor tests (design 5) are the bases on which selection decisions can be made, whereas with the first four concurrent designs only randomisation (designs 6, 7) and existing procedures are used (designs 8, 9). These designs can further be distinguished from each other by being classified on the basis of job performance and predictor test measures gathered shortly after selection (designs 6, 8) or after a delay in time (designs 7, 9). The remaining two designs (10 and 11) are referred to as cross-sectional and shelf designs respectively.

The traditional concurrent validation design (designs 6 to 11) has the advantage that it is practically easy to execute; however its disadvantage lies in the difficulty of conceptually reconciling the research conditions with the conditions under which it will ultimately be used, primarily due to motivational problems, the influence of learning and job-related experience, and the restriction of criterion and predictor variance. The latter, however, does not necessarily constitute a threat to external validity. Whether the restriction of range (the homogeneity of the validation sample versus the homogeneity of the applicant sample) constitutes a problem depends on the selection design to which the findings of the validation design will be generalised. The resultant effect is thus that, with the validation of an assessment instrument on a representative sample of the current employees, this sample cannot be considered representative of the (unselected) applicant population due to the impact of the aforementioned factors. The obtained results of the validation study can thus not simply be generalised to the general (unselected) applicant population. The above dilemma may to some extent be alleviated, however, if the applicant population is defined in terms of the population of already screened individuals (implying a multiple hurdle selection design) instead of the population of unselected individuals.

The typical predictive validation design (designs 1 to 5) has the disadvantage that it is practically difficult to execute, but has as its advantage that it is conceptually reconcilable with the typical situation in which the instrument is ultimately utilised, primarily therein that its variance is not restricted, the effect of motivational problem is reduced, and the problem of learning and experience is eliminated. It is thus implied that a representative sample of (unselected) applicants can reasonably confidently be considered as a representative sample of the unselected applicant population, but that it is practically difficult to obtain both predictor (X) and criterion (Y) measures for such a sample.

In practice, however, the distinction between predictive and concurrent designs seems vague; for reasons of simplicity and practicality concurrent designs are too often substituted for predictive designs. Yet high concurrent validity does not necessarily imply high predictive validity and hence it cannot be used as a substitute (Blum & Naylor, 1968). Nevertheless, debate still rages around which method seems to be the most preferred. Guion (1965, p.20) argues that "the present employee method is clearly a violation of scientific principles". Barrett, Phillips and Alexander (1981) disagree, however. They argue that the correlation coefficient obtained in concurrent validation designs provide as relatively accurate estimates as those obtained in predictive validation designs. Moreover, the so-called "missing persons problem" (individuals who have failed to get the job or keep it, and those that have been promoted out of it) (Guion, 1991) represents a restriction of range problem, which means the appropriate correction formulas can be applied in an attempt to get the two coefficients to agree. Nevertheless, the aim should be the use of a research design yielding the most accurate estimate of the validity coefficient, the regression of the criterion or predictor battery, selection fairness and selection utility as they would apply to the selection design.

Internal and external validity are the two most prominent criteria in terms of which the validation design should be evaluated. Internal validity, viewed from the restricted interpretation of validation designs, refers to the confidence with which the systematic variance in the intermediate criterion can be attributed to the variance in the independent variable(s) of interest. Various factors jeopardising the internal validity of a research design have been identified:

- The extent to which the research design fails to control variance, that is failure in its ability to maximise systematic variance, minimise error variance and control extraneous variance (Kerlinger, 1986); and
- The extent to which statistical power (Cohen, 1977) is decreased.

Cook, Campbell and Peracchio (1991) furthermore identify statistical conclusion validity and construct validity as two additional threats to the validity of a validation design interpreted more broadly. In identifying construct validity as a threat to the internal validity of a more extensively defined validation design, Cook, Campbell and Peracchio (1991) effectively endorse Landy (1986) and Ellis and Blustein's (1991) opposition to the trinitarian approach to validation research. Whereas internal validity constitutes a necessary requirement in the evaluation of research findings, it does not, however, suffice to establish the credibility as empirical evidence in the defense of selection procedures. In addition to the internal validity, the external validity of the research design also needs to be established to ensure sufficient proof in cases of litigation where an attempt is made to argue the equity and efficiency of selection procedures.

The external validity of the validation design is, given the applied nature of the research, of critical importance since it affects the validity and the credibility of (implicit) claims made with regard to the selection procedure. External validity is defined as the degree of confidence with which the conclusion of the operational hypothesis could be generalised to other units of analyses, circumstances, treatments of the independent variable(s) and/or measurements of the dependent variable(s). More specifically, external validity can be defined as the degree of confidence with which results of a specific empirical validation study can be generalised to a specific area of application (Campbell & Stanley, 1963). The core concept utilised in the specification of the area of application that the validation study is meant to simulate is the applicant population.

The definition of the term "applicant population" depends on the positioning of the new selection procedure relative to the one already in use, i.e. it depends on whether the new selection procedure would be integrated with the current procedure, substituted, or added to the current selection programme (Boudreau, 1991). It thus depends on the selection design.

With the focus on the applicant population, generalisation is problematic in that it involves the extrapolation beyond the investigator's specifically defined area of empirical investigation (Campbell & Stanley, 1963; Cook, Campbell & Peracchio, 1991). Generalising beyond the limits set by the validation investigation is always scientifically risky as such a generalisation may lead to incorrect inferences on the applicability of the research results to other subjects, places and times. Hence the evidence supplied by the validation study can theoretically never completely justify generalisations. Nevertheless, an attempt to generalise is unavoidable in the context of applied research (Campbell & Stanley, 1963).

Campbell and Stanley (1963, p.17) advocate that external validity is threatened by the potential specificity of the effect of the independent variable on the dependent variable to features of the research design not shared by the area of application. A number of factors jeopardising the external validity of research designs can be identified (Blum & Naylor, 1968; Campbell, 1991):

- The extent to which the actual or operationalised criterion contains random measurement error;

- The degree to which the actual criterion is deficient and/or contaminated; and
- The extent to which the validation sample is a representative, unbiased sample of the applicant population in terms of certain attributes such as knowledge and motivation.

The area of application is characterised by a sample of actual applicants from the applicant population. The concern in this sample of actual applicants lies with "estimating the individual's actual contribution to the organisation, not an indicator of it attenuated by measurement error" (Campbell, 1990, p.694). To the extent that the above threats do operate in the validation study but do not apply to the area of application, the validity coefficient obtained in the validation study cannot be generalised to the actual area of application. Therefore, not making appropriate corrections will lead to the observed validity coefficients being biased (Schmitt, Hunter & Urry, 1976). The use of sample statistics to estimate the population parameter is accepted under conditions of measurement reliability, sufficiently large sample sizes and sample unbiasedness. These three conditions are, however, not usually satisfied in validation investigations. The research design thus becomes important to the extent that it allows for the data collection and data analysis to permit inferences from the simulation to the application (Guion, 1991). The Guidelines (1998) advocate that appropriate adjustments be made to the validity coefficient to correct it for the attenuating effect of predictor and criterion unreliability and range restriction so as to avoid the under- and over-estimation of validity (Society for Industrial Psychology, 1998). Likewise, Campbell (1990, p.701) recommends that:

> If the point of central interest is the validity of a specific selection procedure for predicting performance over a relatively large time period for the population of job applicants to follow, then it is necessary to correct for restriction of range, criterion unreliability and the fitting error by differential predictor weights. Not to do so would introduce considerable bias into the estimation process.

A further relevant, yet separate, function of the research design, is that it guides the formulation of statistical hypotheses as a quantification of the operational research hypothesis. It is, by implication, not practically feasible to proceed with a quantification of the entire population. Therefore, a representative sample of the applicant population is selected. The nature of the population is implied by the choice of the selection design; the nature of the sampling frame is implied by the choice of the validation method.

Two issues are relevant in a discussion on validation sampling. One is the representativeness of the validation sample. The representativeness of the sample is dependent on the type of sampling procedure used to select the validation sample; on the definition of the applicant population which in turn is dependent on the position of the experimental test (X) relative to the existing test (E) in the selection procedure; and on the validation design used. The other relevant issue is the statistical power of the subsequent statistical analysis.

Given the statistical null hypothesis and the alternative hypothesis, two possible decisions can be taken on H_0, namely to either not reject H_0 or to reject H_0. In Nature, one of two possible conditions exist: either H_0 is true, or H_0 is false. Table 3.2 below portrays the various possible decision outcomes.

Table 3.2 Taxonomy of possible decisions on H_0

Decision	**Hypothesis given to be true**	
	H_0 true	**H_0 false**
Reject H_0	Type I error with probability $\leq \alpha$	Correct decision with probability $= 1 - \beta$
Fail to reject H_0	Correct decision with probability $\geq 1 - \alpha$	Type II error with probability $= \beta$

(Toothaker, 1986, p.338)

It is in this context that statistical power can be defined and interpreted as the probability $(1 - \beta)$ of rejecting H_0 if H_0 is false (Toothaker, 1986). Thus:

$$P(\text{reject } H_0 | H_0 \text{ false}) = 1 - \beta$$

In the context of validation investigations, and assuming an *ex post facto* correlational design, the derivation of statistical power typically proceeds in terms of two primary inferential statistical analyses, namely in terms of Pearson correlation analysis (simple, first-order correlation analysis) and in terms of multiple regression analysis.
Cohen (1977) has developed tables for the determination of the required sample size for various statistical analysis techniques in order to achieve a desired level of power, given fixed values for the remaining conditions affecting power.

In the case of the first-order correlation analysis the statistical power $(1 - \beta)$ of the t-test of H_0: $\rho = 0$ is dependent on (Cohen, 1977; Cohen and Cohen, 1975):

1. The sample size (n);
2. The significance level (β);
3. The presumed effect size (ρ); and
4. The nature of the alternative hypothesis (whether H_a is stated directional or non-directional).

If choices are made on the desired level of power and on points 2 - 4 above, the required sample size can be read off from tables developed by Cohen (1977).

In the case of multiple regression analyses, the power of the F-test for H_0: $P = 0$,
$(1 - \beta)$ is dependent on:

1. The sample size (n);
2. The choice of significance level (α);
3. The number of predictors in the equation (u);
4. The desired effect size $\{f^2 = R^2_{y \cdot b}/[1 - R^2_{y \cdot b}]\}$.

If choices are made on the desired level of power and points 2 - 4, the required sample size can be determined by reading off L from a table developed by Cohen (1977) and by solving the following equation:

$$n = L[1 - R^2_{y \cdot b}/R^2_{y \cdot b}] + u + 1$$

Alternative tables exist to obtain the statistical power of an analysis performed on data obtained from a specific sample with the remaining conditions fixed at specific levels.

When power is found to be insufficient, the researcher has an option to revise the investigation in order to increase the statistical power primarily by increasing the sample size and possibly by increasing the significance level (Cohen & Cohen, 1975). Thus the primary value of determining the statistical power of an analysis lies in its value as a pre-investigatory procedure.

Questions on the sample size and statistical power have found their way to cases in litigation. Specifically, the issue under consideration is the whether the size of the sample is large enough to avoid the unacceptable likelihood of Type II error (accepting H_0 and concluding a phenomenon not to be true in the population when it is). In an attempt to improve statistical power, the goal is thus to obtain a large enough sample for it to provide a validity coefficient "with an acceptably small margin of error in estimating the population parameter" (Guion, 1991, p.354).

3.8 STATISTICAL ANALYSES

The process of validation has thus far resulted in the research hypothesis being operationalised via a valid, deductive argument. A research design and the validation method have been chosen. Statistical research hypotheses have been formulated. A representative validation group has been sampled and the predictor and criterion variables have been measured. The resultant data set is now to be statistically analysed. The purpose of the data analysis is to examine (a) the validity of the performance hypothesis, (b) the derivation of a selection decision rule and (c) the establishment of its equity and efficiency. The quality of the validation investigation depends as much on the appropriateness of the data analysis as on the data collected (Society for Industrial Psychology, 1998).

The validity of the performance hypothesis is examined through the calculation of a validity coefficient or validity coefficients. The validity of a selection assessment instrument is demonstrated by a correlation, i.e. the validity coefficient calculated between the predictor and job behaviour (Guion, 1991); hence it demonstrates the extent to which the substitute represents the ultimate criterion. The further the correlation graduates towards +/-1, the more the substitute is representative of the ultimate criterion. The magnitude of the validity coefficient consequently indicates the practitioner's degree of knowledge concerning the ultimate criterion. Yet with only fallible and incomplete information available, the decision-maker has to contend with the challenge of correctly predicting the expected outcome with a probability less than unity. Nonetheless, in an effort to maximise the individual's contribution to organisational effectiveness, information available from valid predictors can be used to make reasonably accurate predictions of information not yet available (Guion, 1991).

The evaluation of the validity coefficient proceeds partly statistically and partly through subjective judgement. The rationale behind the stated hypotheses; the adequacy of the criterion, the sample and the research design; the standardisation of procedures; and the risk of Type I or Type II errors are factors which should be considered in evaluative judgement (Guion, 1991).

In an evaluation of the validity coefficient (r_{xy}) in a simple bivariate case, the following factors that affect the size of the correlation should be considered:

- The correlation coefficient is computed on the assumptions of linearity and homoscedasticity. Violating the assumptions of linearity and homoscedasticity will lead to underestimates of population values (Guion, 1991). The extent to which these assumptions are met should thus be examined through scatter and residual plots;
- The validity coefficient should be investigated for underestimation due to restriction of range. Correcting for restriction of range poses some problems, however, in that the choice of the correction formulae require knowledge of the source of curtailment (Thorndike, 1949; Thorndike, 1982). Guion (1991) mentions three guiding principles for correcting for restriction of range, namely the greater the range restriction, the greater the need for correction; the higher the correlation in the restricted sample, the lower the resultant bias, and the less the need for correction; and with an increase in the sample comes a decrease in the bias in corrections, because the summary statistics used in the equations will be more reliable;
- The validity coefficient should be examined for underestimation due to unreliability in the predictor and especially unreliability in the criterion. Unless both predictor and criterion reliability is extremely high, the fully and partially attenuated validity coefficient should be calculated and reported alongside the uncorrected validity coefficient; and
- The validity coefficient should be examined for positive or negative bias due to systematic criterion contamination. The nature of the effect of the criterion contaminating factor (Z) will depend on the magnitude and sign of r_{xz}, r_{yz} and r_{xy}. The effect of criterion contaminating

factors can be assessed by calculating partial or semi-partial correlation coefficients and reporting them alongside the uncorrected validity coefficient.

The importance of these factors lies in the fact that the aim in a validation study is to approximate as closely as possible the correlation between the predictor and actual work success, uncontaminated by measurement error, as it applies to the applicant population.

The validity coefficient should be interpreted in terms of its magnitude and sign and in terms of its statistical significance ($p < 0.05$) to determine whether the results can be attributed to chance or whether the results obtained from the validation sample can be generalised to the population.

The investigation into the significance of the validity coefficient is thus a question about the generalisability of the obtained value to the population of which the validation group is a representative sample. Statistical significance means that the probability of obtaining, from an assumed uncorrelated population ($\rho = 0$), a value c for the statistic r_{xy} in a sample of size n is so small (smaller than 0.05 or 0.01) that the assumption that $\rho = 0$ must be rejected in favour of the assumption that rho is not equal to zero but approximately equal to c ($\rho_{xy} \cong c$). Only if the value of r_{xy} is found to be statistically significant ($p < 0.05$) would interpretation continue in terms of the coefficient of non-determination ($1 - r^2$) and the coefficient of determination (r^2). The former is defined as the proportion predictor-variance not brought about by the constructs on which job success is dependent, but by systematic, irrelevant and random error influences, and the latter is defined as the "proportion of variance in either variable that is associated with the variance in the other variable" (Guion, 1965, p.138).

The coefficient of determination is clearly important for selection in that, from the perspective of the criterion r^2_{xy} indicates the proportion criterion variance explained by the predictor. Effective selection is possible to the extent to which differences in criterion performance are understood and can be explained in terms of factors that can be assessed at the time of (or prior) to selection decision-making. In other words, it assesses the fit of the regression equation to the data it describes. When the fit is perfect, both r and r^2 are 1.00 and all the points will fall on the regression line (i.e. $\sum[Y-E(Y|X)]^2 = \sum e^2 = 0$) (Newton & Rudestam, 1999).

A statistically significant correlation implies that the original research hypothesis is accepted, given the prerequisite of an internally valid research design and valid operational definitions in the deductive argument. The information obtained via the validity coefficient about the strength of the relationship between the predictor (X) and the criterion (Y), however, does not suffice to predict Y from X accurately. In order to be able to predict (intermediate) criterion performance from the obtained performance on the selection instrument, it is necessary to establish not only that there exists a statistically significant correlation between the predictor and work success, but also to describe the nature of the relationship. Information on the strength of the criterion-predictor relationship is provided by the validity coefficient r_{xy} and its derivations; the coefficient of determination, the coefficient of non-determination and the index of forecasting efficiency. The nature of the relationship between a single, dependent variable (Y) and one or more independent variables (X) can be described statistically by means of regression analysis.

There are a myriad of psychological and situational factors that influence the behaviour, and by implication the performance, of the individual. The researcher hypothesises that certain characteristics as measured by the predictor(s) are to a certain degree responsible for, or associated with, variations in job performance as measured by the criterion. To achieve success, the method of selection should reflect the human and situational complexity underlying performance. A solution to this challenge is to simultaneously use a multitude of different measures. The identity of the multitude of attributes that need to be measured is suggested by the performance hypothesis derived from the job description. All of these attributes should therefore be considered for inclusion into the selection battery, provided the preceding correlational analyses corroborated the hypotheses derived from the job description.

The use of multiple predictors, however, raises the question on how to combine these various measures to come to a selection decision or selection assignment (Cronbach & Gleser, 1965). Thus, the question on the combination of predictors must first be answered.

A selection strategy, or selection decision function (Cronbach & Gleser, 1965) refers to an explicit or implicit rule dictating, conditional on available information, whether an applicant should be rejected or accepted, or whether and what further information should be collected (Gatewood & Feild, 1994; Muchinsky, 1983).

The nature of the selection strategy depends on the manner in which multiple selection information is combined for decision-making. The following actuarial selection strategies are traditionally distinguished (Gatewood & Feild, 1994; Milkovich & Boudreau, 1994):

- Multiple regression strategy;
- Multiple cut-off strategy;
- Multiple hurdle strategy;
- Profile comparison strategy; and
- Hybrid strategies.

Multiple linear regression represents an extremely useful and versatile set of statistical analysis techniques for the analysis of data from *ex post facto* research designs. The multiple linear regression strategy represents the most widely accepted approach in the combination of predictor information.

Generally, the objective of multiple linear regression analysis is to find a linear composite of independent variables/predictors that would maximally be correlated with the dependent variable and would minimise the squared errors of prediction (Newton & Rudenstam, 1999).

In the parameter the multiple regression of Y on X_i can be expressed as follows:

$$E[Y|X] = \alpha + \beta[X_1] + \beta[X_2] + \ldots + \beta[X_i] + \ldots + \beta[X_p]$$

Because the interest lies in the prediction of the composite criterion (Y) from an array of predictors (X_i), the nature of the covariation of X_i and Y in the population should be established. However, the regression equation for the population is not directly obtainable as the population is not accessible in its totality. Thus, the values of the regression coefficients for the population are approximated from the sample of applicants by means of the least-squares method. The linear regression strategy attempts to combine linearly the smallest combination of predictors for the explanation of maximum variance in the criterion. The method of least-squares calculates the regression coefficients so that the sum of the squared deviations of the Y values from the regression equation is a minimum, i.e. the sum of the squared residuals must be a minimum (Cohen & Cohen, 1975; Ghiselli, Campbell & Zedeck, 1981).

The following types of multiple regression are typically distinguished (Newton & Rudenstam, 1999):

- Standard multiple regression;
- Hierarchical multiple regression; and
- Statistical/stepwise multiple regression.

These different types of multiple regression differ in terms of the allocation of the dependent variable variance to the various independent variables/predictors and in terms of who determines the order in which the independent variables are entered into the regression equation (Tabachnick & Fidell, 1989).

In the case of standard multiple regression, all the independent variables are simultaneously entered into the regression equation. Only unique dependent variable variance is allocated to each independent variable. R^2 reflects shared Y-variance; it is therefore not allocated to any predictor. The question, therefore, is whether each effect would significantly explain variance in the dependent variable when added to a regression model already containing all of the remaining p - 1 effects.

F-values based on the SAS Type II or Type III sum of squares provide the appropriate test statistic to test the following null hypotheses for a model containing three predictors:

$$H_{01}: \beta[X_1] = 0 \mid \beta[X_2] \neq 0, \beta[X_3] \neq 0$$
$$H_{02}: \beta[X_2] = 0 \mid \beta[X_1] \neq 0, \beta[X_3] \neq 0$$
$$H_{03}: \beta[X_3] = 0 \mid \beta[X_1] \neq 0, \beta[X_2] \neq 0$$

In the case of hierarchical multiple regression, the order in which independent variables are entered into the regression model is determined by the researcher on theoretical/logical grounds. All Y-variance explained by an independent variable at its point of entry that has not yet been explained by any effect already entered into the model is allocated to that independent variable. The proportion of Y-variance a predictor explains therefore depends on its point of entry. The question, therefore, is whether an independent variable significantly explains additional Y-variance when entered into a regression model that is not explained by those variables already in the model.

F-values based on Type I sum of squares provide the appropriate test statistic to test the following null hypotheses, assuming three predictors entered into the sequence X_1, X_3, X_2:

$$H_{01}: \beta[X_1] = 0 \mid \beta[X_2] = 0, \beta[X_3] = 0$$
$$H_{02}: \beta[X_3] = 0 \mid \beta[X_1] \neq 0, \beta[X_2] = 0$$
$$H_{03}: \beta[X_2] = 0 \mid \beta[X_1] \neq 0, \beta[X_3] \neq 0$$

In the case of stepwise multiple regression, the order in which independent variables are entered into the regression model is determined by statistical criteria. All dependent variable variance explained by an independent variable not yet explained by the effects already included in the model is allocated to the particular independent variable. The proportion Y-variance a predictor explains therefore depends on its point of entry into the regression model. The question therefore is whether an independent variable significantly explains variance in Y when entered into a regression model that is not explained by those variables already included in the model.

F-values based on Type I sum of squares provide the appropriate test statistic to test the following null hypotheses, assuming three predictors entered into the sequence X_3, X_2, X_1:

$$H01: \beta[X3] = 0 \mid \beta[X2] = 0, \beta[X3] = 0$$
$$H02: \beta[X2] = 0 \mid \beta[X3] \neq 0, \beta[X1] = 0$$
$$H03: \beta[X1] = 0 \mid \beta[X3] \neq 0, \beta[X2] \neq 0$$

With the statistical/stepwise multiple regression, the goal is to identify the smallest sub-combination of predictors able to explain the greatest proportion criterion variance, i.e. the goal is to identify the smallest weighted combination of predictors which correlate the highest with the criterion (Kleinbaum & Kupper, 1978).

The basic procedure for the development of a test battery is as follows:

The total validation group is randomly divided into two equal groups, termed the validation group and the cross-validation group.

From the matrix of the predictor and citerion-predictor intercorrelations calculated from the data obtained from the validation group, the predictor correlating highest with the composite criterion (Y) is identified. A second predictor that correlates high with Y but low with the first predictor is consequently selected. The regression of Y on the weighted linear combination of the two predictors is subsequently described by means of the least-squares regression equation (Newton & Rudestam, 1999; Tabachnick & Fidell 1989):

$$E[Y|X] = \alpha + \beta_1[X_1] + \beta_2[X_2]$$

The multiple correlation $R_{y\cdot12}$ as the correlation between the composite criterion (Y) and the weighted, linear combination of predictors is calculated and compared with the previous correlation between the criterion and the single best predictor (i.e. r_{xy}). Under the condition that $R_{y\cdot12}$ is significantly higher than $R_{y.12} > r_{xy}$, the possibility of a three-predictor battery is investigated via the least-squares regression equation of:

$$E[Y|X] = \alpha + \beta_1[X_1] + \beta_2[X_2] + \beta_3[X_3]$$

The process of predictor selection from the correlation matrix, the regression analyses and the calculation of multiple correlation coefficients continues until further addition of predictors no longer results in significant increases in the multiple correlation. With the addition of each new predictor to the selection battery, the crucial question is whether the predictor in question significantly explains unique variance in the composite criterion not explained by any other predictor already in the battery (Tabachnick & Fidell, 1989). The selection of predictors into the selection battery terminates when none of the predictors, as yet excluded in the model, significantly explains variance in the composite criterion not explained by the predictors already included in the model.

In the context of selection it is not the individual's specific predicted criterion score that is of primary interest, but rather the position of the predicted criterion score relative to the critical minimum criterion performance (Y_k). It hence follows that any applicant's predicted criterion performance, calculated from the validation group's regression equation, greater or equal to the established, critical criterion performance, Y_k, is considered as a predicted success and shall thus be taken into account in the consideration for selection.

It is, however, also possible to simplify the decision-rule by calculating the critical predictor cut-off X_k from the regression equation given a specified criterion cut-off. This, however, is only possible under the multiple regression strategy when selection is based on a single predictor. X_k can, conditional on the selection ratio, be changed so as to represent a stricter predictor cut-off point. It is thus possible to compare individual predictor scores with the critical, X_k predictor score and only to consider the individuals falling above the cut-off point ($X > X_k$; assuming $r_{xy} > 0$ and a positive composite criterion) for selection, whereas those individuals falling below the cut-off point ($X < X_k$) will be rejected.

Criterion-referenced norm tables should be calculated from the appropriate regression equation to enable the criterion-referenced interpretation of predictor scores in terms of $E[Y|X_i]$ and $P[Y<Y_k|X_i]$.

The calculation of the validity coefficients, the testing of their significance, the determination of the selection battery and the multiple regression equation occurs in terms of the specific validation group for which both the predictor and the criterion variables are available.

The multiple regression equation calculated for the final battery represents the manner in which the measures of the predictors will be combined for selection decision-making. Furthermore, the multiple correlation coefficient ($R_{y\cdot 123\ldots t}$ $[0 \leq R_{y.123\ldots t} \geq 1]$) represents the validity coefficient of the battery. The coefficient of determination (R^2) will again be used for further interpretation. R^2 still represents the proportion of criterion variance explained by the linear, weighted combination of predictors.

Whenever simple or multiple regression equations are used, they are developed to predict optimally the criterion for an existing group of persons. To estimate the extent of subsequent shrinkage in predictive accuracy, it is important that the process of cross-validation is utilised prior to the implementation of the regression equation in the selection procedure (Gatewood & Feild, 1994; Ghiselli, Campbell & Zedeck, 1981).

Cross-validation is essential in establishing confidence in the weights derived from a multiple regression analysis. The regression weights are appropriate for the group for which they have been developed. Whether they are effective in predicting the criterion in another sample from the same population is determined by the process of cross-validation (Ghiselli, Campell& Zedeck, 1981). Guion (1965) emphasises that cross-validation is necessary before any decision-rule is used for decision-making purposes. If the shrinkage is small and the corrected R is still sufficiently large, the multiple regression equation can be used with confidence as the basis for the selection strategy.

Two further aspects deserve attention in the development and validation of selection procedures. They are the utility and the fairness of selection decision-making based on the decision-rule derived actuarially through regression analysis from the validation sample. The latter two aspects are subsequently discussed.

3.9 UTILITY

Blum and Naylor (1968, p.44) define the utility of a selection device as:

> the degree to which its use improves the quality of the people being selected beyond what would have occurred had that device not been used.

More specifically, however, viewed from a strategic perspective on personnel selection, utility analysis focuses on the determination of institutional gains and losses anticipated from various courses of action. When having to choose among (selection) strategies, human resource practitioners must choose the strategy that will maximise the expected utility for the organisation across all possible outcomes by estimating the utility associated with the various possible outcomes. Estimating utility has traditionally been the Achilles' heel of utility analysis research (Cronbach & Gleser, 1965).

In an investigation into institutional costs and expected gains of selection procedures, the focus falls on the strategy involved in the decision function. Selection strategies serve to guide decisions about applicants made by human resource practitioners. Selection strategies should, therefore, be evaluated in terms of their "total contribution when applied to a large number of decisions" (Cronbach & Gleser, 1965, p.23). Decision options in this context, therefore, refer to the programmes/strategies involved in assigning applicants to treatments rather than to individual applicants themselves (Boudreau, 1991; Cronbach & Gleser, 1965). When considering the possible implementation of a selection procedure, the value of doing so must therefore be compared with the benefits that would accrue if an alternative procedure would be implemented or retained.

The appropriate utility calculation depends on the situation in which the selection programme is utilised. Thus the meaning afforded to the concept "applicant population" is also dependent on the way the new selection procedure is used relative to the selection requirements already in use. Cronbach and Gleser (1965) identify three possibilities that could apply when assessing the utility of a selection procedure:

- All selection requirements employed will continue to be used and the new system will be added to it;
- The new selection procedure will replace the current (prior) selection requirements in use; or
- The new and the existing procedures will be integrated/combined with each other.

Multi-attribute utility (MAU) models represent a decision theory approach to personnel selection and they serve as conceptual vehicles for "describing, predicting, and explaining the usefulness or desirability" of selection decision strategies (Boudreau, 1991, p.624). Selection utility models, as a variation of MAU models, are characterised by the following structural components (Boudreau, 1991):

- A set of decision options representing alternative procedures under consideration;
- A set of attributes reflecting the characteristics of the outcomes affected by the decision options which the decision-maker considers relevant;
- A utility scale measuring the level of each attribute produced by each decision option (thereby reflecting the value of the attribute);
- A pay-off function reflecting the weight assigned to each attribute, as well as the rules in terms of which each attribute is combined, for the derivation of the total utility value for each option; and
- A set of parameters characterising the decision situation in which the selection strategy will be used.

With a set of options available, utility models specify the attributes in terms of which the relevant outcomes can be described (Boudreau, 1991). The attribute domain is somewhat vaguely defined by Cronbach and Gleser (1965, p.22) as "all the consequences of a given decision that concern the person making the decision (or the institution he represents)." As it would virtually be impossible to consider all the possible decision outcomes and consequences, the selection utility model, like most models, simplifies reality by omitting the less important attributes. Therefore, only those attributes are considered that are most aligned with the (decision) objectives of the organisation.

Efficiency and equity (Milkovich & Boudreau, 1994) are two categories of human resource objectives in terms of which the attributes can be identified and included in the set of salient attributes. Efficiency-related attributes reflect the organisation's ability to maximise output while minimising input, whereas equity refers to those attributes that affect the fairness of the selection procedure (Boudreau, 1991; Milkovich & Boudreau, 1994). A small set of efficiency-related attributes seems to have been regarded as sufficient to characterise the outcomes of selection procedures. At least three basic attributes should be considered to ensure the adequacy of the selection utility model (Boudreau, 1991, p.628):

- "Quantity - the number of employees and time periods affected by the consequences of program options;
- Quality - the average effect of the program options on work force value, on a per-person per-time-period basis; and
- Cost - the resources required to implement and maintain the program option."

A utility/pay-off scale (the third of the structural components) for each attribute is established for the purpose of quantifying the level of each attribute associated with each decision option. Although subjective or objective information can be used to quantify the desirability of the attribute levels associated with each option (Boudreau, 1991), the use of a subjective scale would ignore the need to translate the consequences of the selection procedure into the everyday financial language of line managers (Cascio, 1991b). The quantity attribute is usually expressed in person-years, whereas the cost attribute is usually measured in an appropriate monetary unit (Boudreau, 1991). Although debate has emerged around the appropriate scale for the quality attribute, consensus seems to exist as to the appropriateness of Rand-cent per person-year as a quality scaling.

The quality pay-off scale focuses on the economic value of increments in the quality of the labour force. The quality of employees manifests itself through a combination of the following output dimensions (Boudreau, 1991):

- Quality of production;
- Quantity of production; and
- Cost of production.

By implication, organisations could derive economic benefit from labour force quality enhancement through (Boudreau, 1991):

- Increases in the quality of production;
- Increases in the quantity of production; and
- A reduction in production costs.

A utility scale for the quality attribute is thus appropriately defined if the definition incorporates any one, or a combination, of the above. There are at least three different interpretations of the pay-off scale for the quality attribute, namely (Boudreau, 1991):

- Pay-off as cost reduction;
- Pay-off as increased value of output; or
- Pay-off as increased profits.

The fourth component of the selection utility model is the pay-off function, specifying the weights attached to each attribute and the rules in terms of which the weighted attributes are combined to establish the total utility for each decision option under consideration (Boudreau, 1991). Such rules may vary in terms of their weighting; however, they should be expressed in the same units as the decision objective. It therefore seems appropriate to remark that the utility scale of the selection utility model should be aligned to the yardstick of profitability. Boudreau (1991, p.629) remarks that:

> (Utility analysis) research has usually focussed on productivity-related outcomes and thus has adopted payoff functions reflecting dollar-valued productivity and program costs. The payoff function may be considered a variant of the cost-volume-profit models used in other managerial decisions to invest

> resources. The utility of human resource management program options is derived by subtracting cost from the product of quantity times quality, with the program exhibiting the largest positive difference being preferred.

The pay-off function thus allows the selection strategy to be evaluated in terms of its total contribution to organisational profitability relative to the capital used to generate the profit.

With time, selection utility models have progressed from basic to very detailed and complex contemporary utility models. The following utility models can be differentiated in terms of their interpretation of the pay-off resulting from a selection strategy:

- Pay-off defined in terms of the validity coefficient;
- Pay-off defined in terms of the success ratio;
- Pay-off defined in terms of the expected standardised criterion performance level; and
- Pay-off defined in terms of a monetary-valued criterion level.

3.1.9 The Validity Coefficient Utility Model

The validity coefficient approach has the longest history in the evaluation of the utility of selection procedures and forms the building block of all subsequent utility analysis models. As mentioned earlier, the validity coefficient has two related indices, namely the index of forecasting efficiency ($\in=1-[1-r^2_{xy}]^{\frac{1}{2}}$) and the coefficient of determination. Both lead to the conclusion that only very large differences in the validity coefficient produce important differences in the value of a test. As Cronbach and Gleser (1965, p.31) argue:

> The index of forecasting efficiency describes a test correlating 0,5 with the criterion as predicting only 13% better than chance; the coefficient of determination describes the same test as accounting for 25% of the variance in outcome. Thus it appears that in using these two indices, great improvements in testing would be necessary to have a substantial effect on organisational outcomes.

The general objective of the classical validity utility model, expressed in terms of R^2 and $\in=(1-[1 - r^2]^{\frac{1}{2}})$, is concisely summarised by Cascio (1991a, p.291), who states that:

> The best selection battery is the one that yields the highest multiple R between predicted and actual criterion scores.

In its attempt to minimise selection errors (failing to select a candidate that should have been hired and/or selecting a candidate that should not have been hired in the first place) this model places emphasis on measurement and prediction.

The usefulness of a test depends on its ability to provide information to improve decisions measured in terms of valued decision outcomes. The evaluation of the usefulness of a selection system in terms of the validity coefficient, viewed from a decision theory perspective, is deficient, as only one attribute, namely the accuracy of the prediction (expressed as the shared variance between two normally distributed variables), is considered (Boudreau, 1991).

The value of the selection strategy is, in effect, measured by the extent to which the squared deviations of observed criterion scores from a predicted linear regression are minimised. Positive or negative deviations from the regression line are considered equally undesirable. Predicting deviations means over-predicting or under-predicting a candidate's future performance and, as both are considered costly to the organisation, both should be avoided. Selection errors can thus result from attempts to predict such deviations.

These models, in which pay-off is based on the validity coefficient, however, fail to reflect formally the quantity, quality and cost attributes. Because none of the attributes of the selection system is explicitly considered, no pay-off function exists for the combination of different attributes either. The validity coefficient thus serves as the sole utility value (Boudreau, 1991). As a result human resource practitioners are forced to take into account alternative selection utility models.

3.9.2 The Taylor-Russell Utility Model

Taylor and Russell (1939) proposed a utility analysis model designed to indicate the usefulness of a test as a function of the situation in which it is used. The Taylor-Russell model reflects three attributes of the selection situation. That is, the overall utility of a selection device is a function of three parameters, namely the validity coefficient, the selection ratio (SR) and the base rate (BR). The Taylor-Russell model, in combining these three parameters, assumes a linear, homoscedastic regression of a normally distributed standardised criterion on a normally distributed standardised predictor. It is the area under the bivariate normal curve that is of interest in the derivation of the success ratio. The success ratio can be defined as the probability of success on the criterion conditional on surpassing the critical cut-off on the predictor (X_k), i.e. $P[Y \geq Y_k | X \geq X_k]$ if Y is positive and the regression of Y on X is positive.

The Taylor-Russell utility model defines selection utility in absolute terms as:

$$\text{Absolute utility} = [Sr' - BR] \times 100\%$$

and in relative terms as:

$$\text{Relative utility} = ([Sr' - BR]/BR) \times 100\%$$

Whenever a quota exists, i.e. when a restriction is placed on the total number of applicants that may be accepted, the selection ratio becomes significant. The more the SR graduates toward zero, the more favourable selection becomes from the perspective of the organisation, as there are more applicants than positions available, and the organisation finds itself in a position to be selective in terms of whom they decide to hire. Figure 3.1 below illustrates the effect of the SR on the success ratio given a fixed validity.

In each case (Figure 3.1), X_c represents a cut-off score on the predictor. It is evident from Figure 3.1 that, given a high SR, predictors should possess a high validity in order to increase the percentage successful among those selected. However, predictors with very low validities can be useful, too, if the SR is low and the organisation needs to choose only the best candidates available. Although it may appear that, given a particular validity and BR, decreasing the SR should always be advocated, it is not that simple as this forces the recruitment and selection programmes to be expanded, which may not be cost effective (Cascio, 1991b).

In cases of unrestricted selection, the SR becomes flexible (Cascio, 1991a). Under these conditions the important consideration becomes the determination of the cut-off score on the predictor. Increasing the cut-off score decreases the probability of erroneously accepting individuals, whereas lowering the cut-off score decreases the probability of erroneous rejections (Cascio, 1991a). The objective thus becomes to minimise the total number of decision errors. Cronbach and Gleser (1965) and Ghiselli *et al.* (1981) have established a procedure for determining the cut-off score with the objective of minimising decision errors. The cut-off point is the point at which the predictor distributions of those succeeding and those failing on the criterion (i.e. $Y \geq Y_c$ vs $Y < Y_c$) intersect each other (Blum & Naylor, 1968).

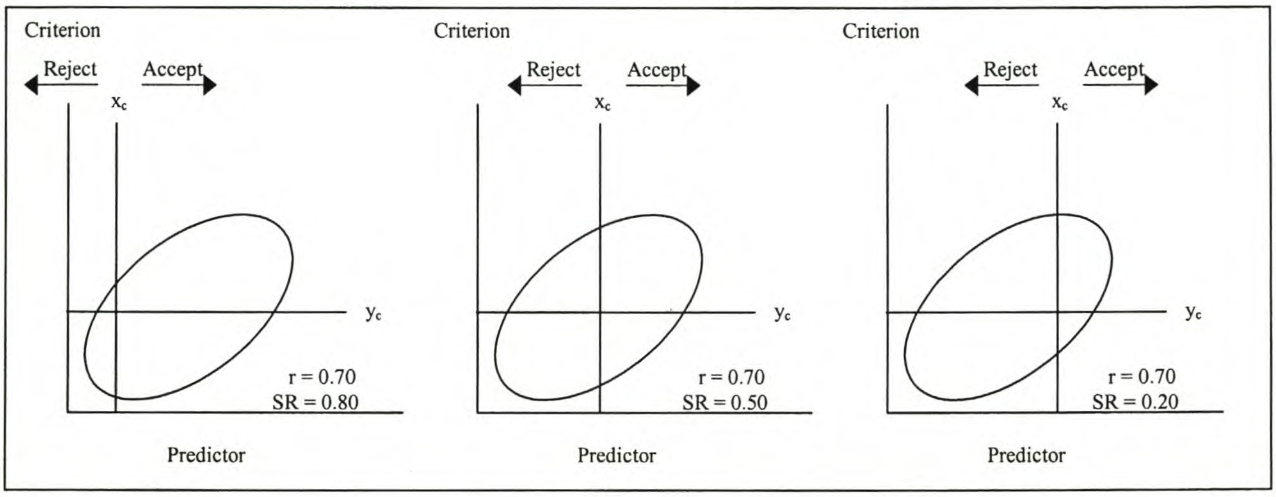

Figure 3.1 Effect of varying selection ratios on a predictor with a given validity (Cascio, 1991b, p.181)

This procedure set out by Cronbach and Gleser (1965) and Ghiselli *et al.* (1981) serves as a general principle in situations in which two types of decision error (erroneous acceptances and erroneous rejections) are considered to be equally costly (See Figure 3.3).

Taylor and Russell (in Blum & Naylor, 1968; Boudreau, 1991; Cascio, 1991a, 1991b) moreover advocate that the selection efficiency is also affected by the BR characterising the selection situation. Meehl and Rosen (in Cascio, 1991a) reiterate the above and emphasise the importance of the BR in the evaluation of the efficiency of a selection procedure.

Figure 3.2 below illustrates the effect of the varying BR on the efficiency of the selection procedure. From Figure 3.2 it is evident that the higher the BR, the more difficult it is for a selection procedure to improve upon random selection.

Y_c (Figure 3.2 below) represents the minimum criterion performance standard (the minimum cut-off score) and its relative position in the criterion distribution determines the BR. The value of the cut-off point, however, should not be defined arbitrarily (Boudreau, 1991). Rather, the criterion cut-off and the BR should be based on the applicant population (the proportion of the applicant population that would exceed the level of minimum acceptable criterion standards if hired) and on the level of minimum acceptable criterion standards determined by the organisation aligned to their needs.

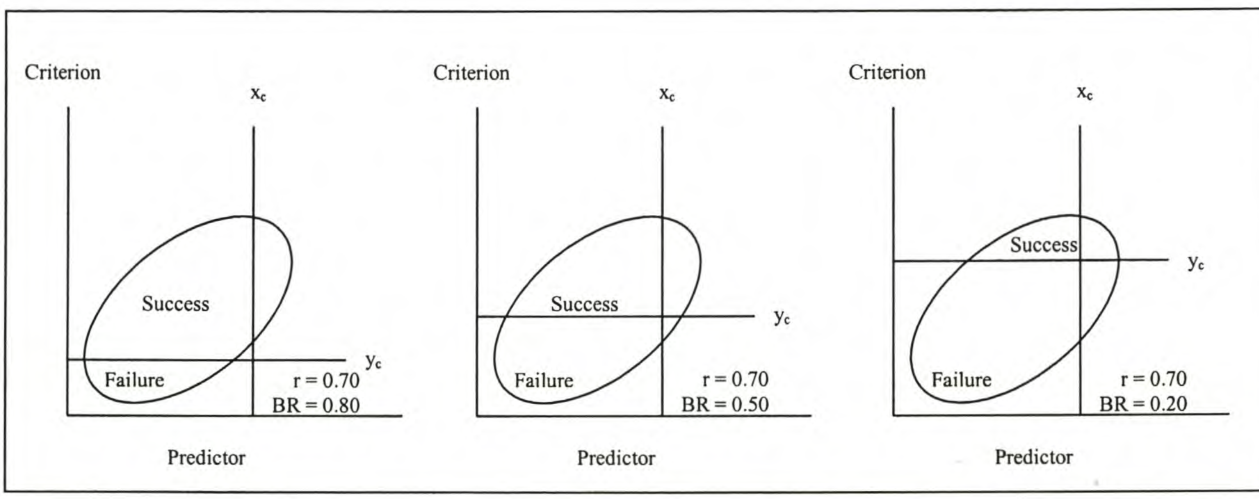

Figure 3.2 Effect of varying base rates on a predictor with a given validity

(Cascio, 1991b, p.182)

In Figure 3.2 above, a BR of 0.80 is set which would make it difficult for any selection procedure to improve upon the success ratio achieved through random selection. This is illustrated by the fact that a selection procedure should have a validity coefficient of 0.45 in order to be able to bring about a 10% improvement in the success ratio given a SR of 0.50. The same tendency is observable with regard to a very small BR. When the BR is 0.20, the SR 0.50 and the validity coefficient 0.40, the percentage improvement in the percentage selected applicants successful under the new selection programme is a mere 10% in comparison to the percentage selected applicants successful under the conditions of the old selection procedure (Cascio, 1991a, 1991b).

Cascio (1991a) furthermore argues that the largest utility in absolute terms can be attained with a new selection procedure with a BR of 0.50. This phenomenon exists because the variance of a dichotomous variable is equal to pq, where p and q refer to the proportion of successes and failures respectively.

The variance is a maximum when p = q = 0.50. Under the condition that all other variables are kept constant, the potential relationship with the predictor increases as the variance increases (Cascio, 1991a). Conversely, the selection efficiency of a selection procedure, expressed in relative terms, is a maximum when the BR is low.

The Taylor-Russell approach to selection efficiency is diagrammatically portrayed in Figure 3.3 below. The Taylor-Russell approach will be discussed below from the perspective of the empirical parameters of selection efficiency.

The criterion cut-off score in Figure 3.3 divides current employees into a dichotomous distinction of satisfactory (successes) and unsatisfactory (failures). The predictor cut-off score, determined by the SR, defines the proportion of applicants that will be selected by a given level of selectivity. Areas A and C represent correct acceptances and correct rejections respectively, while areas B and D represent erroneous rejections and erroneous acceptances respectively. Two distinct types of decision errors thus exist with great implications for the human resource function, namely erroneous acceptance and erroneous rejection. These two decision errors are, however, inversely related to one another. An increase in the one would necessary lead to a decrease in the other and vice versa. The only solution to minimise both would be to increase the validity coefficient and to change the value of the predictor cut-off score.

The Taylor-Russell utility can be calculated empirically from the data obtained from a validation sample. It is, however, also possible to determine theoretically the Taylor-Russell selection utility in terms of a new selection procedure added to the current procedure from appropriate tables without directly calculating it from the data of the validation group.

The Taylor-Russell utility model is based on the following assumptions:

1. The validity coefficient is calculated via the current employee method;
2. Fixed treatment selection is assumed (i.e. specific treatments assigned to applicants cannot be modified);
3. The percentage erroneous rejections is not taken into account.

4. The criterion (Y) and the predictor (X) are normally distributed;
5. The regression between X and Y is linear and homoscedastic; and
6. The Taylor-Russell model does not choose optimal selection ratios/cut-offs, but rather evaluates those already selected (Cascio, 1991b).

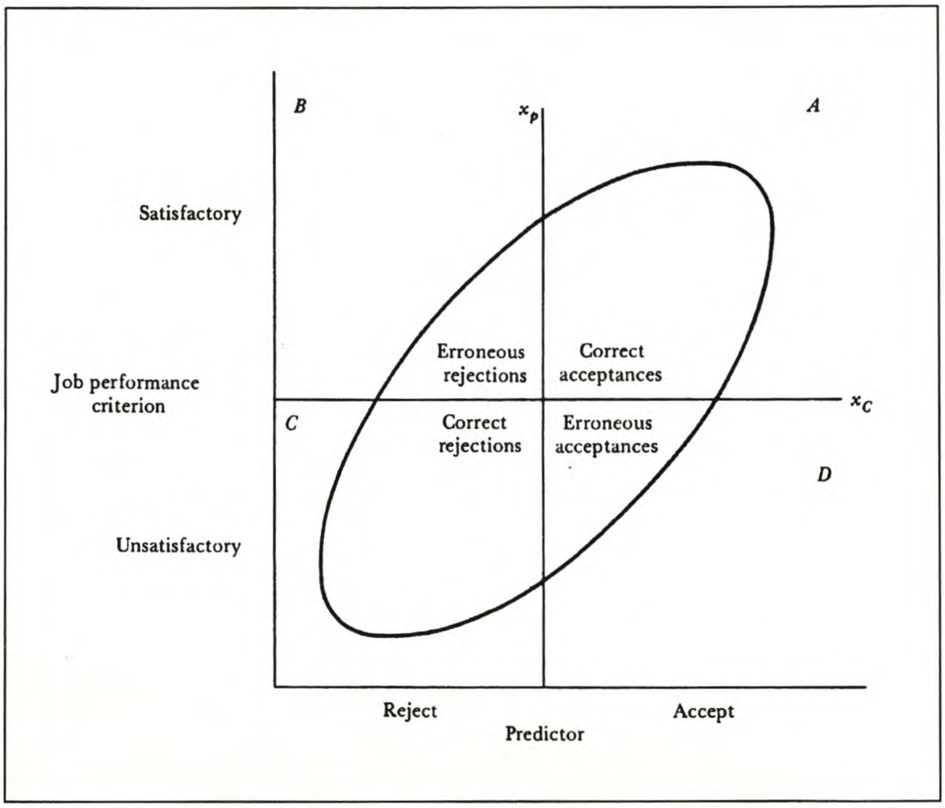

Figure 3.3 Effect of predictor and criterion cut-offs on a bivariate distribution of scores (Cascio, 1991a, p.293)

As the model classifies, criterion performance as dichotomous and demonstrates that the success ratio increases for a fixed validity as the SR decreases, the critique is valid as the above conditions contribute to the success ratio being merely an indication that more people are successful but indeed not how much more successful they are (Cascio, 1991b). The disadvantage of the Taylor-Russell utility model is that it merely gives a description of the selection utility as a percentage; it thus does not give an indication of the size of the actual improvement in the quality of the work force in terms of the criterion scale. Differences in the degree of success are thus ignored.

Another approach toward personnel selection utility is the Naylor-Shine model, defined as the increase in the expected, average criterion score with the use of a selection procedure with a given validity coefficient and SR.

3.9.3 The Naylor-Shine Utility Model

In contrast to the Taylor-Russell utility model (Taylor & Russell, 1939; Boudreau, 1990; Cascio, 1991a), the Naylor-Shine approach (Naylor & Shine, 1965; Boudreau, 1990; Cascio, 1991a) assumes a linear relationship between validity and utility. The Naylor-Shine utility model (1965) interprets selection utility in terms of the expected standardised criterion performance of the selected group of applicants. That is, the higher the validity the greater the increase in the average criterion score for the selected group over and above the score observed for the total (applicant) group for a given, defined cut-off score on a predictor. Unlike the Taylor-Russell model, the Naylor-Shine model does not require the dichotomisation of employees into satisfactory and unsatisfactory groups by means of the specification of a clearly defined cut-off on the criterion dimension that represents the minimum acceptable performance. The major criticism of the Taylor-Russell model, namely that the dichotomisation of the criterion distribution fails to reflect the true range of variation in selectee performance, is thus addressed by the Naylor-Shine model by scaling total utility on a continuous criterion scale expressed in standard score units (Boudreau, 1991,634).

Like the Taylor-Russell model, the Naylor-Shine utility model (Naylor & Shine, 1965) assumes a linear, homoscedastic regression of a normally distributed standardised criterion on a normally distributed standardised predictor. For a standardised criterion (0; 1) and a standardised predictor (1; 0), the regression of the standardised criterion on the standardised predictor can be written as:

$$E[Z_y|Z_x] = \rho[X,Y]Z_x$$

Using the above equation as a basic building block, Naylor and Shine represent a set of tables that specify for each selection ratio:

- ❖ The standardised predictor cut-off corresponding to the SR (ϕ);
- ❖ The height of the ordinate under the normal curve at that point (λ); and
- ❖ The ratio λ/ϕ, representing the mean standardised predictor score of the selected group.

Assume a standardised predictor cut-off Z_{xc} resulting in a SR = ϕ, where the expected standardised criterion performance of the top-down selected applicants can be written as:

$$E(Z_y|E[Z_x|Z_x \geq Z_{xc}]) = \rho[X,Y]E[Z_x|Z_x \geq Z_{xc}]$$

It can be shown (Boudreau, 1991) that, if one assumes a normally distributed predictor and one proceeds with top-down selection, the average standardised predictor score is a function of the proportion of the applicant population falling above the predictor cut-off score (i.e. the SR) and the height of the ordinate at the cut-off. The Naylor-Shine table is based on the fact that, if normality of the predictor distribution is assumed, it can be shown that:

$$E[Z_x|Z_x \geq Z_{xc}] = \lambda/\phi$$

where λ denotes the height of an ordinate under the standardised normal distribution cutting of an upper proportion equal to SR = ϕ. It thus follows that:

$$\begin{aligned} E(Z_y|E[Z_x|Z_x \geq Z_{xc}]) &= \rho[X,Y]E[Z_x|Z_x \geq Z_{xc}] \\ &= \rho[X,Y]\lambda/\phi \end{aligned}$$

The above equation applies whether ρ_{xy} is a zero-order correlation coefficient or a multiple correlation coefficient and X a linear composite (Cascio, 1991b).

The expected standardised criterion performance of the selected group can subsequently be transformed back to the original criterion scale as the expected mean performance improvement by multiplying $E(Z_y|E[Z_x|Z_x \geq Z_{xc}])$ with a standard deviation $\sigma[Y]$ of the composite criterion:

$$\Delta U/\text{selectee} = \rho[Z_x,Y]\sigma[Y][\lambda/\phi]$$

The expected composite criterion performance of the selected group could then be obtained by adding the mean improvement to the mean performance delivered by the alternative/current selection procedure.

The Naylor-Shine table could also be used to determine the SR, X_k and the number of applicants needed to effect the desired improvement on the composite criterion scale (i.e. utility scale), given a fixed number of vacancies. The desired improvement on Y is expressed as a Z score. $Z_y\rho[X,Y] = \lambda/\phi$ is solved and λ/ϕ is located in the Naylor-Shine table and ϕ and Z_{xc} are read off. The latter is then transformed back to X_k and the number of applicants required is computed as the number of vacancies divided by the required SR = ϕ.

The Naylor-Shine utility index indicates the increase in the average criterion performance that is to be expected as the organisation becomes more selective in deciding whom to accept, which is more applicable than the Taylor-Russell utility index. Neither of these models, however, formally integrates the concept of the cost of a selection procedure or the monetary value gained or lost in terms of the utility index. They do, however, imply that larger differences in the percentage of successful employees of larger increases in average criterion scores will yield larger benefits to the employer in terms of money saved.

A variety of criticisms have been raised against the Naylor-Shine model, of which the most obvious is the difficulty of the interpretation of the criterion performance expressed in terms of standard criterion levels/standardised score units. This drawback can, however, be overcome by transforming the average improvement in standardised criterion performance to the original criterion scale. Moreover, the Naylor-Shine model reflects only the difference between the average criterion score of those selected with the predictor/new selection procedure versus the average standardised criterion score that would be obtained without the new predictor. The total value of the programme is thus not computed; merely the performance increments produced by the selection procedure (Boudreau, 1991).

In evaluating the Naylor-Shine model in terms of the three basic selection outcome attributes of quality, quantity and cost, it again becomes evident that neither the quantity of employees and the time period affected by the selection decisions, nor the cost of the programme is explicitly reflected by the model. The quality is taken into account, however, although it is expressed in statistical units and is therefore not easily understandable (Boudreau, 1991).

Human resource managers may conclude from the Naylor-Shine model that the greater the increase in the average criterion score, the greater the advantage to the organisation in terms of the financial returns earned on the money invested in selection. This deduction is not necessarily true, however, as neither the costs to bring about an improvement in the average criterion performance nor the monetary value of a unit increase in criterion performance is considered. Selection, irrespective of the efficiency of the procedure, does not have any merit unless the financial return on the investment made in the procedure is significantly positive.

A comprehensive interpretation of the concept utility should therefore express the R/c value of the increments in work performance brought about by the selection procedure in terms of the cost of producing such increments. Personnel costs continue to consume larger parts of the total business costs, and for this reason human resource practitioners are put under increased pressure to justify new or existing selection procedures in terms of selection equity and selection efficiency and, more specifically, in terms of the relative utility compared to alternative strategies in the attainment of organisational goals (Cascio, 1991a).

3.9.4 The Brodgen-Cronbach-Gleser Utility Model

The Brogden-Cronbach-Gleser utility model interprets selection utility in terms of the performance improvement achieved by the selection procedure expressed on a criterion scaled in a monetary unit. The Brogden-Cronbach-Gleser utility model assumes a linear, homoscedastic regression of a normally distributed criterion, scaled in an appropriate monetary unit, on a normally distributed standardised predictor. Brogden (1949) and Cronbach and Gleser (1965) used linear regression to illustrate the relationship between, on the one hand, the cost of selection, the validity coefficient and the SR of the selection procedure and, on the other hand, the utility of selection procedure. The Brogden-Cronbach-Gleser expressions for selection utility can be developed as follows from the above assumptions:

$$E[Y|Z_x] = \alpha + \beta Z_x$$

Due to the standardised predictor $\alpha = E[Y]$. By definition:

$$\beta = \rho[Z_x,Y](\sigma[Y]/\sigma[Z_x])$$
$$=\rho[Z_x,Y]\sigma[Y]$$

since by definition $\sigma[Z_x] = 1$, consequently:

$$E[Y|Z_x] = E[Y] + \rho[Z_x,Y]\sigma[Y]Z_x$$

The expected mean criterion performance of a top-down selected group of applicants can therefore be expressed (in R/c) as:

$$\begin{aligned} E(Y|E[Z_x|Z_x \geq Z_{xk}]) &= E[Y] + \rho[Z_x,Y]\sigma[Y](E[Z_x|Z_x \geq Z_{xk}]) \\ &= E[Y] + \rho[Z_x,Y]\sigma[Y][\lambda/\phi] \end{aligned}$$

The above equation allows for the computation of the monetary value of average work performance in the selected group. What is needed, however, is an equation that gives the increase in R/c value of the average performance that results from using the predictor. Thus, the monetary worth of the improvement in expected performance over random selection can be expressed (in R/c) as:

$$\begin{aligned} E(Y|E[Z_x|Z_x \geq Z_{xk}]) - E[Y] &= \rho[Z_x,Y]\sigma[Y](E[Z_x|Z_x \geq Z_{xk}]) \\ &= \rho[Z_x,Y]\sigma[Y][\lambda/\phi] \end{aligned}$$

To effect an increase in performance through a selection procedure, however, requires the investment of financial and other resources. To express the benefit (i.e. utility) derived from a selection procedure in financial terms, the worth of the improvement of the expected performance should be adjusted for the cost of the procedure. For the purpose of classification, two cost categories can be identified, namely true costs and potential costs. True costs include the costs involved in the selection of new employees such as recruitment and selection costs, whereas potential costs refer to the costs resulting from erroneous decisions. They thus include the cost of accepting individuals that do not perform successfully in the job as well as the costs involved in the rejection of potentially successful candidates (Dunnette, 1966).

Thus let C represent the true assessment cost per applicant. The marginal or per selectee utility can then be expressed as:

$$\Delta U/\text{selectee} = \rho[Z_x,Y]\sigma[Y][\lambda/\phi] - C/\phi$$

The per selectee utility thus represents the expected R/c benefit of the improvement in performance brought about by the new selection procedure per selected applicant.

The total return or utility for a single time period obtained from the once-off use of the selection procedure to select a single cohort can therefore be expressed (assuming N applicants and a SR = ϕ) as:

$$\begin{aligned}\Delta U &= N\phi(\rho[Z_x,Y]\sigma[Y][\lambda/\phi] - C/\phi)\\ &= N\phi\rho[Z_x,Y]\sigma[Y][\lambda/\phi] - (C/\phi)N\phi\\ &= N\rho[Z_x,Y]\sigma[Y][\lambda] - CN\end{aligned}$$

The single cohort, however, delivers its higher-valued performance not only over a single time period but over T (average tenure of selectees) time periods. If it is assumed that the stream of returns remain constant over T periods, the following expression results:

$$\begin{aligned}\Delta U &= TN\phi\rho[Z_x,Y]\sigma[Y][\lambda/\phi] - \{C/\phi\}N\phi\\ &= TN\rho[Z_x,Y]\sigma[Y][\lambda] - CN\end{aligned}$$

The Brogden-Cronbach-Gleser model developed so far, however, still provides an incomplete description of the monetary valued benefits that would be derived from the implementation of a selection procedure.

The following economic considerations, usually applied to other institutional financial decisions, should also be formally acknowledged by the utility expression:

1. The tax liability faced by (most) organisations on the returns generated by the investment in valid selection procedures;
2. The potential investment returns forfeited on future selection returns;
3. The effect of increased performance on variable costs; and
4. The effect of employee flows produced by consecutive applications of a selection procedure (additive cohort effects).

Boudreau (1991) extended the Brogden-Cronbach-Gleser selection utility model developed above to include the above four aspects.

The standard deviation of the monetary scaled criterion represents the only quantity that could possibly prevent the practical application of the Brogden-Cronbach-Gleser utility expressions. A number of techniques have been proposed to estimate $\sigma[Y]$, including:

- The Schmidt, Hunter, McKenzie and Muldrow Global Estimation procedure;
- The Schmidt and Hunter 40% rule;
- The Eaton, Wing and Mitchell Systems Effectiveness procedure; and
- The Cascio-Ramos (CREPID) procedure.

Of all of these estimation procedures, the most prevalent technique is the Cascio-Ramos (CREPID) procedure.

3.9.5 The CREPID Procedure

The CREPID (Cascio-Ramos Estimate of Performance in Dollars) procedure (Cascio & Ramos, 1986) is based on the assumption that the monetary worth of average performance in a particular position is reflected as the average yearly wage/salary paid to incumbents in that position. The procedure entails breaking down the job into its principal activities, rating the relative contribution each principal activity makes to overall performance and calculating the monetary worth of average performance on each principal activity by distributing the annual wage/salary across principal activities in accordance with the relative contribution to overall performance. It then requires of supervisors to rate each employee's job performance on each principal activity. The resulting ratings are then translated into estimates of a monetary value (R/c) for each principal activity. The sum of the monetary value assigned to each principal activity equals the economic value of each employee's job performance.

The CREPID procedure (Boudreau, 1991; Cascio, 1991b) encompasses the following specific steps:

1. The principal activities/key performance areas have to be identified/defined from a job description. Job analysis is thus required to define explicity the principal activities (or critical work behaviours) which encompass at least 10% of the total work time (Cascio, 1991b);
2. Ratings are obtained from a panel of m subject matter experts (SME) for each principal activity on a 7-point graphic rating scale on:
   - the amount of time spent on each performance area or the frequency with which incumbents have to attend to various performance areas (T/F_i); and
   - the importance of each of the performance areas (I_i);
3. The mean of the m (T/F_i and I_i) ratings for each principal activity has to be multiplied to obtain an importance rating for each principal activity;
4. Relative weights w_i are calculated for each performance area by the expressing the products of step three above in terms of the sum of the products, summed across performance areas. The ratings are multiplied so that, if an activity is never done or is of no importance, the relative weight for that activity is zero (Table 3.3). The assignment of relative weights to each principal activity allows the practitioner to allocate proportional percentage shares of average yearly salary to the principal activity;
5. The monetary value of average performance on each principal activity (R_{c-wi}) is determined by multiplying the yearly wage/salary with the relative weights associated with each performance area;
6. After the relative weights and the monetary value (R/c) of each principal activity have been calculated, the level of each employee's performance on each of the key performance areas is rated. The actual performance of each member of the validation sample on each performance area is rated on a 0 - 200 graphic rating scale (${}_{cr}Y_{ij}$; i=1, 2, 3, …,p; j=1, 2, 3, …,n). The higher the ratings of each key performance area, the greater the economic value to the organisation;
7. The performance ratings are then transformed to a 0 - 2 point graphic rating scale by dividing the original appraisal by 100, so that the average performance now equals 1;
8. The product of the transformed performance ratings on the p performance areas and the monetary worth of the average performance on each performance area is calculated for each individual (i.e. $[{}_{cr}Y_{ij}][R_{c-wij}]$; i = 1, 2, 3, …, p; j = 1, 2, 3, …, n]);
9. The monetary worth of the overall actual performance is computed by summing the monetary valued performance ratings across the performance areas for each individual (i.e.$\sum[{}_{cr}Y_i][R_{c-wi}]$; i = 1, 2, 3, …,p; j = 1,2, 3, …,n)

10. The standard deviation of the distribution of n monetary scaled overall performance scores is subsequently calculated. A large standard deviation indicates that the difference in the monetary value in the performance of an employee falling at the 50^{th} percentile (P_{50}) of the criterion distribution and an employee falling on the 85^{th} percentile (P_{85}) is large. Under conditions of large differences in monetary-valued job performance, selection decision errors will result in substantial financial losses and a valid selection procedure will demonstrate the greatest utility.

Table 3.3 CREPID rating scales for principal activities

1. *Time/frequency*: Please rate each principal activity on the 0–7 scale shown below. Stepping back and looking at the whole job, say, over a one-year period, how would you allocate the principal activities in terms of the time/frequency with which each is done?

0	1	2	3	4	5	6	7
very rarely		sometimes		often			very often

2. *Importance*: Please rate each principal activity on a 0–7 scale that reflects, in your opinion, how important that principal activity is to overall job performance. Use the scale below as a guide to help you rate.

0	1	2	3	4	5	6	7
of no importance		moderately important		very important			of greatest importance

Principal Activity	Time/ Frequency	×	Importance	=	Total	Relative Weight (%)
1	4.0		4		16.0	16.8
2	5.0		7		35.0	36.8
3	1.0		5		5.0	5.3
4	0.5		3		1.5	1.6
5	2.0		7		14.0	14.7
6	1.0		4		4.0	4.2
7	0.5		3		1.5	1.6
8	3.0		6		18.0	19.0
					95.0	100.0%

(Cascio, 1991b, p.217)

If the selection utility of the selection procedure is satisfactory, the possibility of negative discrimination still needs to be investigated. The results of an investigation into the fairness of a selection procedure could, furthermore, affect the utility of a selection procedure.

3.10 FAIRNESS

Practical, legal and social changes that have occurred over the past few years in South Africa have begun to have a significant impact on many facets of personnel selection. The whole issue of fairness in personnel selection has become highly relevant since the applicant populations for many jobs and educational opportunities have become increasingly multi-cultural. The controversy surrounding fairness arises from the fact that fairness in the workplace is not an absolute that can be proven to exist or not. There is no universally accepted definite constitutive definition of fairness; rather there are many conceptions each underpinned by a particular value system (Ghiselli *et al.*, 1981; Holburn, 1991; Taylor, 1992). The concept of discrimination (or fairness) is, moreover, problematic due to the difficulty experienced in solving this elusive ethical dilemma psychometrically. Furthermore, a number of different fairness models exist, each defining the concept of fairness differently and each differing in its implicit ethical position and consequently prescribing varying solutions to the problem.

There are three implicit ethical positions from which statistical definitions of selection fairness are derived. A fairness model based on one of the ethical positions set out below, dictates a formal investigative procedure to assess the fairness of a selection strategy, should such a strategy be challenged legally. The three ethical positions are unqualified individualism, quotas and qualified individualism (Hunter & Schmidt, 1976, p.1053-1054):

Unqualified individualism refers to the position which holds selection to be ethically sound if individuals with the highest predicted performance are selected from available information utilised for scientifically valid predictions. From the "unqualified individualism stance", unethical selection can occur in two ways, namely through failure to use an available, more valid predictor and through knowingly failing to use a more valid prediction equation based on the available information.

Quotas refer to the demographic representativeness of those individuals being selected. The point has been made that "…in a city whose population is 45% black and 55% white, any selection procedure that admits any other ratio of blacks and whites is 'politically biased' against one group or the other" (Hunter & Schmidt, 1976, p.1054). By implication, quotas may thus be based on population percentages or on "other factors irrelevant to the predicted future performance of the selectees" (Hunter & Schmidt, 1976, p.1054).

Qualified individualism refers to the opposition of discrimination on the basis of race, gender, national origin and religion, where it is imperative to refuse to use the above as predictors even if it were scientifically valid to do so. The qualified individualist recognises (possible) misinterpretations from the use of a single regression line (as in the Cleary fairness model below) but still omits any of the above factors from his selection decision rule. The qualified individualist therefore relies solely on measures of ability, personality and motivation in his predictions of future performance, without any reference to group membership. This position, however, seems to be internally contradictory.

The objective of selection is to provide a means by which some individuals may be selected and others rejected. That is, the basic goal of selection is discrimination. The crucial point, however, is whether the discrimination is fair or unfair. Although there is no universally acceptable definition of "unfair", the following explanation by Arvey and Faley (1988, p.7) provides a foundation for the discussion:

> Unfair discrimination or bias is said to exist when members of a minority group have lower probabilities of being selected for a job when, in fact, if they had been selected, their probabilities of performing successfully in a job would have been equal to those of non-minority group members.

Equal employment litigation and regulations are significant considerations in personnel selection. Pivotal to South African labour law has been the advent of the Employment Equity Act (1998), which has as its goal compulsory non-discrimination. Yet issues such as fairness and bias are often misinterpreted, if not overlooked, and much confusion reigns as to the way fair assessment procedures should be implemented. Selection procedures are viewed as fair if they do not unfairly discriminate against members of a specific group or unfairly lower the probability of members of a minority or disadvantaged group of being selected (Arvey & Faley, 1988). The Act (1998), therefore, underlines the importance of the implementation of effective and defensible procedures in a manner which will indicate the justifiability of selection procedures utilised in organisations. Empirical evidence generated reliably by methodologically sound research needs to be obtained in order to verify the appropriateness, reliability, usefulness and meaningfulness of the inferences made from test scores of (valid) assessment instruments, thereby limiting, if not eliminating, possible cases of litigation.

The Guidelines (Society of Industrial Psychology, 1998), emphasising the significance of the establishment of equity and efficiency in the personnel selection procedure, suggest that the shifting burden of proof model of the USA is relevant for the South African context. The statutory laws and official guidelines concerning the employment practices in the USA are aimed at allowing all individuals equal employment opportunities irrespective of gender, race, ethnic group or age. It is thus the objective to eliminate the possibility that individuals are not employed as a result of their status on one or more of these biographical variables. The most important American statutory law in this regard is the Civil Rights Act of 1964 (Arvey & Faley, 1988), specifically Title VII of the Act which, in its objective and contents, is synonymous to Articles 9 and 23 of the Bill of Rights of the SA Constitution (1996, p. 7 and 10 respectively):

> *Equality*
>
> 9. (2) The state may not unfairly discriminate directly or indirectly against anyone on one or more grounds, including race, gender, sex, pregnancy, marital status, ethnic or social origin, colour, sexual orientation, age, disability, religion, conscience, behaviour, culture, language and birth.
>
> (3) No persons may unfairly discriminate directly or indirectly against anyone on one or more grounds in terms of subsection (3). National legislation may be enacted to prevent or prohibit discrimination.
>
> (4) Discrimination on one or more of the grounds listed in subsection (3) is unfair unless it is established that the discrimination is fair.
>
> *Labour relations*
>
> 23. (1) Everyone has the right to fair labour practices.

The Bill of Rights (1996) specifies the specific, non-negotiable grounds on which equitable selection procedures may not be based - it protects minorities in as far as discriminating behaviour disadvantages job applicants, prospective employees or the current workforce. Furthermore, where they are allegedly unjustly discriminated against, a *prima facie* case of indirect discrimination (adverse impact) or direct discrimination (disparate treatment) must be established by the plaintiff. The defendant, on the other hand, must demonstrate the non-discriminatory business-relatedness of his actions and decisions by establishing the validity and utility of the assessment instrument and the fairness of the final personnel decision. The defendant must, therefore, be able to refute any charges made against him by providing legally permissible, empirical evidence for the employment practice under scrutiny.

The Equal Employment Opportunity Commission (EEOC) of the USA is responsible for the application of Title VII of the Civil Rights Act. EEOC cases can be launched against organisations if the plaintiff's opportunity to employment is, on face value, disadvantaged or if the individual is deprived of employment opportunities on the basis of gender, race, age, ethnic origin. An examination into the American approach to EEO litigation is recommended, as the USA litigation sets an example for South Africa in the sense that, because it has existed for such a long time and because of the level of sophistication with which selection procedure issues (e.g. fairness and utility-related issues) are dealt with, it represents a framework from which South Africa can learn, where the positives can be applied and the negatives can be avoided.

In order to be able to successfully prove a *prima facie* case of adverse impact (practical significance of unequal impact on members of a protected/minority group), the plaintiff can make use of two types of statistical data to show that on face value the employment practice seems unfair. Most statistical comparisons that have been used by plaintiffs in an effort to establish a *prima facie* case of discrimination can be subsumed under the two broad categories of *Flow Analysis Statistics* and *Stock Analysis Statistics* (Arvey & Faley, 1988).

Concerning the *Flow Analysis Statistics*, the plaintiff must offer statistical evidence showing significant existing differences in the proportion of actual applicants from majority and minority groups being hired. That is, proof is needed to indicate that the selection ratio of the two groups differs significantly (Arvey & Faley, 1988; Ghiselli et al. 1981) (see Figure 3.4).

Number of successful minority applications		Number of successful non-minority applicants
--------------------------------------	Compared to	--
Total number of minority applications		Total number of non-minority applications

Figure. 3.4 Comparison of proportion of applicants

(Arvey & Faley, 1988, p.75)

A variation of the Flow Analysis Statistic is based on the pass/fail rate of potential applicants for the job, based on whether the minority group in question possesses the particular set of qualifications compared to non-minority members as shown in Figure 3.5. A disparate impact complaint serves as sufficient proof for a *prima facie* case against an organisation, based on the low face validity of the selection procedure. The onus of proof then rests on the employer to show the contrary, that is to prove a validation study has been conducted in the justification of the set selection requirements. This once more highlights the significance of the psychometric validation procedure (hence the psychometric audit) in personnel selection.

Number of minorities in relevant labour markets with particular qualifications		Number of non-minorities in relevant labour markets with particular qualifications
-------------------------------------	Compared to	---
Total number of minorities in relevant labour market		Total number of non-minorities in relevant labour market

Figure 3.5 Comparison of proportion of applicants with particular qualifications

(Arvey & Faley, 1988, p.76)

A second strategy (*Stock Analysis Statistics*) used in the establishment of a *prima facie* case of disparate impact is to offer statistical evidence comparing an organisation's workforce in terms of race/gender/ethnic ratios with the general population of a particular geographical area based on the geographical scope of the employer's recruitment practices (Arvey & Faley, 1988) (see Figure 3.6).

Number of minorities employed		Number of minorities in relevant geographical area
------------------------------------	Compared to	--
Total number of employees		Total number of people in relevant geographical area

Figure 3.6 Comparison of proportion of applicants in particular relevant geographical area

(Arvey & Faley, 1988, p.76)

A variant of stock analysis statistics is concentration statistics which are based on whether there are significant differences in the distribution of particular groups throughout the levels of a particular organisation compared to how they are distributed in similar organisations (Arvey & Faley, 1988).

Disparate treatment, on the other hand, refers to deliberate unequal treatment toward members of a minority group members. The emphasis therefore falls on the plaintiff having to establish the employer's motivation as discriminatory in nature. Plaintiffs must thus establish either directly or inferentially that they were intentionally treated less favourably. To establish *prima facie* disparate treatment, inferential evidence must contain the following (*McDonnel Douglas corp.* v. *Green*, 1973, in Arvey & Faley, 1988):

- He/she is a member of a protected/minority group;
- He/she had applied for the advertised position;
- He/she had been rejected in spite of being suitably qualified;
- The vacant position had not been filled; and
- The employer continues to search for an appointee with qualifications similar to those of the plaintiff.

Once a *prima facie* case has been demonstrated, the burden of persuasion shifts to the defendant to defend his employment practices. This does, therefore, imply that an attempt to prove disparate treatment or impact does not necessarily imply unfair selection or unfair labour practice. However, if the *prima facie* case is based on the disparate impact doctrine, the defendant may chose between one of three options, namely to demonstrate the business necessity of his actions by referring to the validity and the utility of the selection instrument as well as the fairness of decisions based there upon; to remove the disparate impact by adopting the cut-off scores; or to choose an equally valid employment practice with less disparate impact (Arvey & Faley, 1988). The latter two options seem to be questionable in as far as they seem to lower the utility of the selection procedure and ignore the criterion-referenced interpretation of predictor information respectively.

It is evident that the use of different statistical approaches and their potentially differing results in an attempt to combat organisational discrimination indicates that discrimination is not "hard fact" (Arvey & Faley, 1988, p.78), but rather that it depends on the statistics used by the courts in establishing the presence of disparate treatment or adverse impact. An excerpt from *Dendy v. Washington Hospital Centre* (1977, in Arvey & Faley, 1988, p.78) supports the above assertion:

> The phases "prima facie case" and "discriminating effect" are terms of art without specific meaning. Lacking only pretence of scientific exactness, they merely serve as guideposts to assist in singling out employment practices for which it is appropriate to ask employers to offer justifications. The precise point at which statistical data casts sufficient suspicion on an employment practice to require explanation by an employer is not fixed by any rule of thumb.

Furthermore, it is important to foster an awareness in South Africa of the actual level of sophistication with which fairness-related issues/disparities can be handled, which would undoubtedly also improve the effectiveness of selection procedures. More and more sophisticated procedures have been introduced in the USA in employment discrimination cases where the courts have gone as far as to calculate the phi coefficient to test for predictor and criterion correlation significance, to investigate predictor utility, and to determine prediction bias by performing co-variance analysis to examine differences in slopes and intercepts of group specific, separate regression lines.

The Guidelines (Society of Industrial Psychology, 1998, p.27) provide valuable clarification of the fairness concept by remarking that:

> Fairness is a social rather than psychometric concept. Its definition depends on what one considers to be fair. Fairness has no single meaning, and, therefore, no single statistical definition. Fairness or lack thereof is not the result of the assessment instrument or predictor, nor is it the property of the assessment procedure used. Fairness is the total of all the variables that play a role or influence the final personnel decision. This can include the test, predictor, integration of data, recommendations based on these data or the final decision made by line management.

Taking into account the absence of a universally acceptable interpretation of the concept of fairness, it is nevertheless necessary to obtain an intellectual grasp on the concept. Such an understanding, however, may be impaired by the fact that fairness is associated with, yet not identical to, the concept of bias. Bias in tests refers to a systematic over- or under-estimation in the value of a test parameter (Holburn, 1991), thus the systematic distortion of measurement (Osterlind, 1989). In other words:

> Bias is defined as a systematic error in the measurement process. It affects all measurement in the same way, changing measurement – sometimes increasing it and other times decreasing it… It is a technical term and denotes nothing more or less than the consistent distortion of a statistic (Osterlind, 1989, p.301).

For reasons of clarification three types of bias are identified.

Construct bias of a test is closely tied to construct-related validity and can be summarised as follows:

> Part of construct validation typically involves the consideration of the internal structure of the test parts and the extent to which the observed structure is consistent with the theoretically expected structure. The natural extension of this approach to bias considerations involves the extent to which the construct being measured is comparable across groups (Owen, 1986, p.9).

In other words:

> Bias exists in regard to construct validity when a test is shown to measure different hypothetical traits (psychological constructs) for one group than for another or to measure the same trait but with differing degrees of accuracy (Owen, 1989a, p.29).

Construct bias can be said to exist if the factor structure or underlying measurement model differs significantly across groups. Structural equation modeling (Jöreskog *et al*, 1993) provides the most satisfactory technique for evaluating assessment techniques for construct bias.

Test items that are statistically demonstrated to be more difficult or easy overall for a given group may be regarded as suffering from *item bias.* Item bias as traditionally defined can be said to exist if the average score obtained on an item for members of one group differs from the average score of the other group by more or less than expected from the performance on the other items of the same test. This definition is, however, unconditional (Taylor, 1987) on testees' ability level, since item bias can only be identified on the basis of the relation between the item concerned and the other items on the test (Owen, 1989b). However, as Owen (1986) points out, since population differences in the average test score may reflect true differences regarding the measured construct, differences in average performance cannot be interpreted as sufficient evidence of test bias. Therefore, item bias should more specifically be defined as follows:

> an item is generally considered biased if equally able members of different groups have unequal chances of success on the item (Subkoviak, Mack, Ironson & Craig, 1984, p.49 in Owen, 1989).

The above view of item bias is supported by Kulick and Dorans (1984); Petersen (1980), Rudner and Geston (1982); and Scheuneman (1980) (in Owen, 1989a, 1989b).

Thus, an item is biased against members of a group if the expected performance on the item is lower for persons in that group than for persons of a similar level of ability in the other group. It is, however, important to realise that the above definition is set against a precondition with regard to the testee's ability level. That is, only persons with the same ability level are compared with one another.

The sources of bias can be reduced or eliminated by either repairing items or discarding them from further consideration. The two most prominent bias detection techniques that can be used for the reduction or the elimination of item bias include the chi-square (χ^2) method and the methods based on the item response theory (Osterlind, 1989; Owen, 1986, 1989a).

Predictive bias refers to the systematic errors in the prediction of scores on a criterion which are associated with group membership. Predictive bias is probably the most important kind of bias for test users due to its direct implications for selection decisions and the fairness of employment practices. According to Jensen (1980, p.381-382):

> a test is a biased predictor if there is a statistically significant difference between the major and minor groups in the slopes, or in the intercepts, or in the standard error of estimates of the regression lines of the two groups, when these regression parameters are derived from the estimated true scores of persons within each group.

Predictive bias is therefore absent only if the slopes of the regression lines are the same in different groups; the intercepts of the regression lines are the same; and the errors of prediction in the different groups are the same.

A variety of fairness models have been proposed (Arvey & Faley, 1988; Cascio, 1991a; Petersen & Novick, 1976); all of them examine the effect of the selection decision function on the different subgroups contained in the applicant population by a simulation of the selection process on a representative sample of the applicant population. Only two of the models will be examined, namely:

- ❖ The regression or Cleary model; and
- ❖ The equal risk or Einhorn-Bass model.

3.10.1 The Cleary Fairness Model

The Cleary fairness model (1968) is based on Cleary's definition of what constitutes unfairness/biasedness and its implication for selection practices, all which are based on the assumptions that (Peterson & Novick, 1976):

- ❖ Criterion and predictor scores are available for each of the subgroups. By implication, all applicants are selected regardless of their performance on the predictor; and
- ❖ The criterion is a reliable, relevant and unbiased measure of applicants' performance.

Cleary (1968) works from a regression framework to formalise a unique and sophisticated approach to test discrimination. Cleary (1968), however, clouds the whole debate on test fairness through the unfortunate use of the term test bias as a synonym for the fair use of a test. Cleary's (1968) approach to fairness suggests that a selection model is fair if the expected job performance of minority and majority group members are not systematically over- or under-predicted and the applicants having the highest expected performance are being selected. Cleary (1968) thus defines a test as being used fairly only if the decision-rule used for selection decision-making acknowledges and makes provision for differences in the regression of performance on the selection battery should such differences exist. In other words:

> A test is biased for members of a subgroup of the population if, in the prediction of a criterion for which the test was designed, consistent nonzero errors of prediction are made for members of the subgroup. In other words, the test is biased if the criterion score predicted from the common regression line is consistently too high or too low for members of the subgroup. With this definition of bias, there may be a connotation of "unfair", particularly if the use of the test produces a prediction that is too low (Cleary, 1968, p.115).

The regression model thus advocates that unfairness in selection practices occurs if the predicted criterion score from the common regression line is consistently too high or too low for the subgroup members. That is, unfairness exists if the performance of members of a subgroup is systematically being under-predicted and the performance of members of the other subgroup is systematically being over-predicted. The fundamental question of the classical regression model is thus whether the separate regression lines fitted for the two groups significantly differ in terms of intercept and/or slope, or whether the use of a single, common regression line computed for the entire group provides an accurate description of the data of the subgroups (see Figure3.7).

Consider a white and a black group member, each of whom has a test score of A on the predictor as shown in Figure 3.7 where:

- ❖ $E[Y|X_W]$ represents the predicted score for the white group member based on the regression equation of the white sample;
- ❖ $E[Y|X_B]$ represents a predicted score for the black group member based on the regression equation for the black sample; and
- ❖ $E[Y|X_T]$ represents the predicted score based on the regression equation of the combined group.

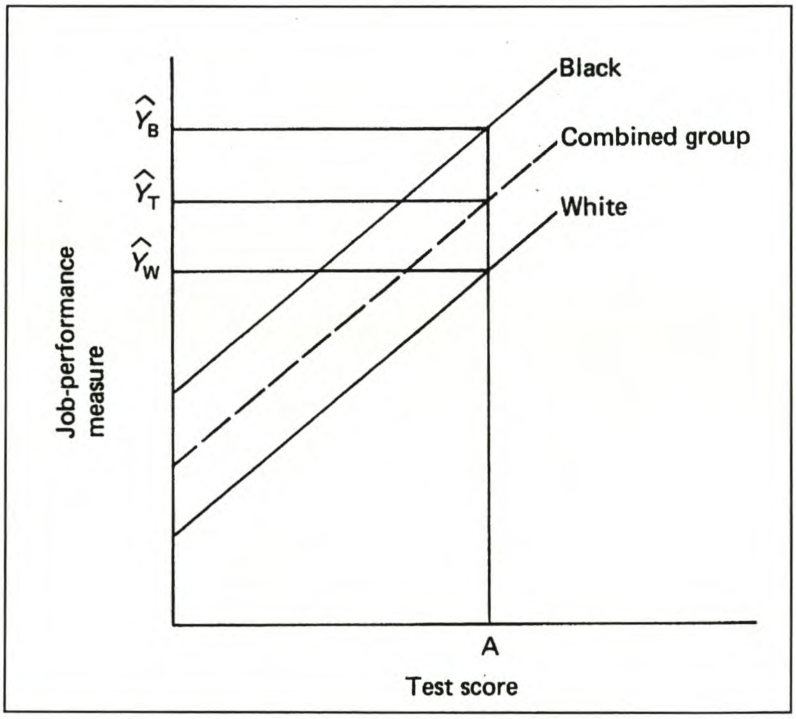

Figure 3.7 Unfair test discrimination illustrated using regression lines

(Arvey & Faley, 1988, p.132)

From Figure 3.7 it is evident that if the white regression line were used to predict the criterion scores of both the black and white groups, the performance of the black group would be under-predicted by an amount of the difference between the black group's expected score and the expected score assigned by the regression line of the white group. Similarly, if a regression line based solely on the total group were used, it would under-predict the criterion scores of the black group. Thus, if a common regression line were to be adopted to hire individuals with the highest predicted criterion score, those belonging to the black group would have a much lower probability of being selected. For the two groups to be equal in their probability of being selected under conditions of different predicted criterion performance, the group whose regression line under-predicts the others' performance is only truly equal in their expected performance if the under-predicted group's test scores are higher than the other group's by an amount related to the amount of under-prediction.

Of further value for a greater understanding of fairness and the practical implications of the Cleary fairness model, is the similar research done by Ruch (1972, in Arvey & Faley, 1988), who documents that, where differences in intercept values between black and white groups occur, the intercept is in fact lower for the black group than for the white group. Contrary to popular belief, this difference indicates that a common regression line would in fact over-predict the expected job performance of the black group members as indicated in Figure 3.8 below.

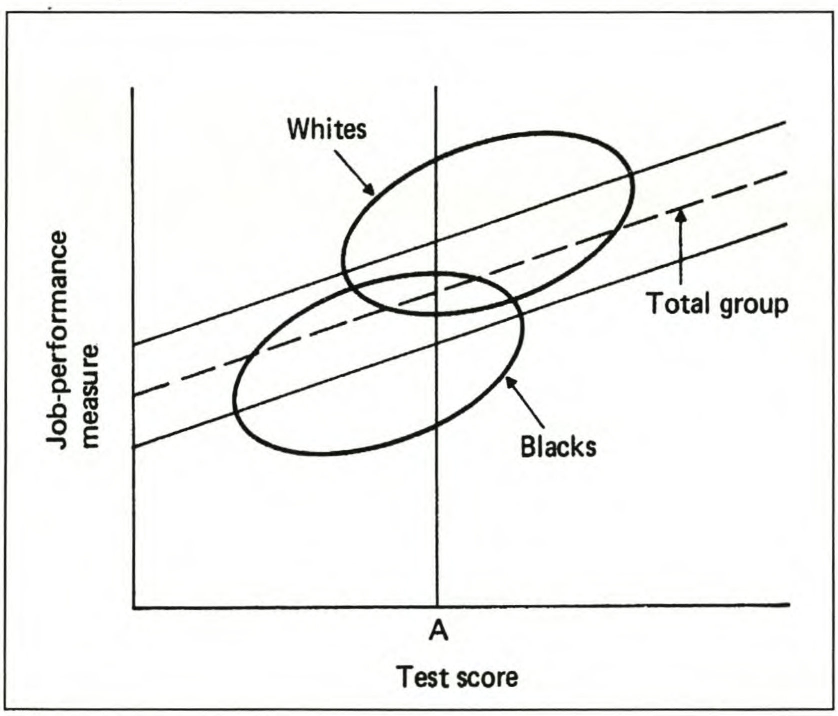

Figure 3.8 Situation in which a black group is overpredicted when a regression line based on the total sample is used

(Arvey & Faley, 1988, p.136)

The use of a common regression line will thus lead to relatively more black applicants being hired due to their over-predicted criterion scores compared to a situation where separate regression lines had been used.

It is, however, important to realise that over-prediction and under-prediction may occur depending on what specific point the regression line is being considered. Figure 3.9 represents a situation in which a non-valid (zero slope) test is used for the white group which is, however, valid for the black group. If a common regression equation is used to make prediction from both groups at point A, the black subgroup members will be under-predicted. However, if predictions are made at a substantially lower score (point B), the white subgroup members will be under-predicted (Figure. 3.9). Also, if the slopes are not equal, separate equations must be used or the multiple regression equations must be expanded for the inclusion of the effect of possible moderator effects.

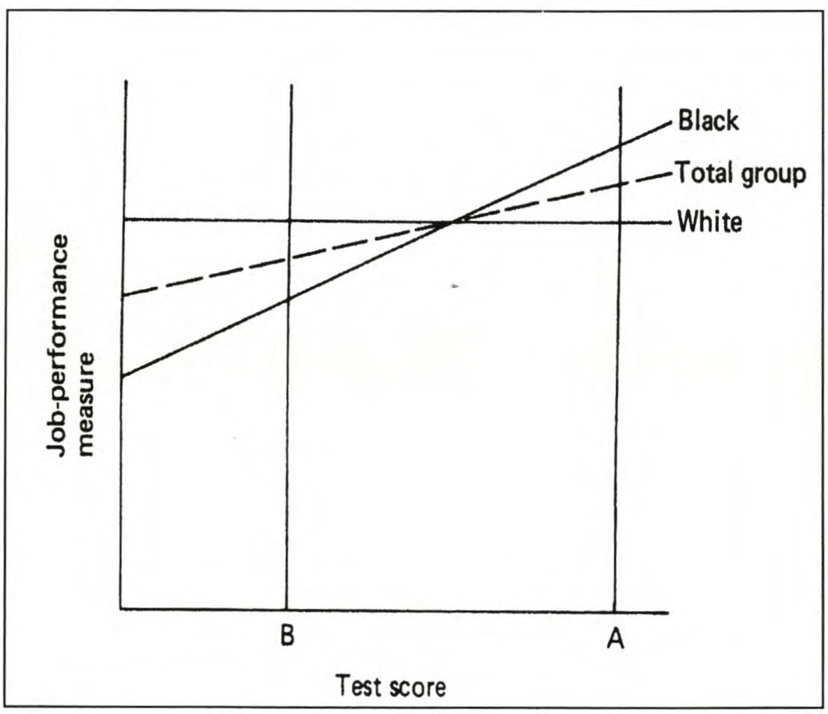

Figure 3.9 Example of unfair discrimination at different points on regression lines

(Arvey & Faley, 1988, p.133)

According to Cleary (1968) fairness can thus be achieved in two ways:

1. By using a test in which the regression lines do not differ, where the same predicted score is made regardless of which subgroup an individual may be a member of (Figure 3.10 below);
2. Fairness is achieved by making predictions based on the different regression equations in cases where regression equations differ by subgroup. Hunter and Schmidt (1976, p.1055) thus recommend that:

> if the regression lines for blacks and whites are not equal, then each person will receive a statistically valid predicted criterion score only if separate regression equations are used for the two races.

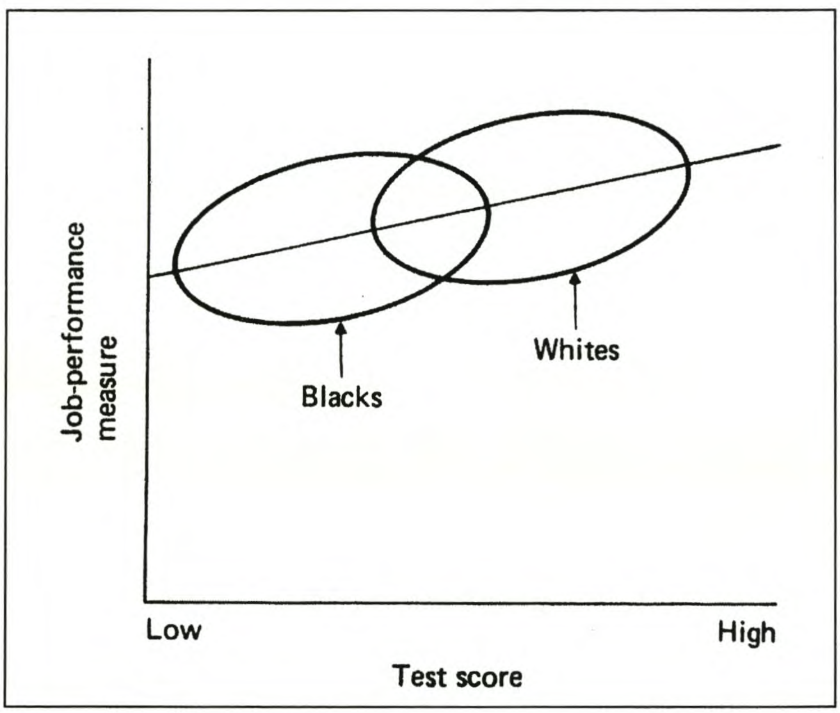

Fig. 3.10 A fair selection procedure using the Cleary definition

(Arvey & Faley, 1988, p.134)

For both alternatives, the selection strategy would thus be to hire those individuals with the highest predicted criterion scores regardless of which equation was used in making the predictions (Arvey & Faley, 1988). The question as to whether the use a single or common regression line is representative of the description of the subgroups can be established by the use of dummy variables to represent group effect through main and interaction terms in multiple regression analysis.

In the examination of fairness of the selection decision rule in terms of the Cleary interpretation of fairness, consider two groups π_1 and π_2 and a linear regression of a (composite) criterion on a single predictor or on a weighted linear combination of predictors. On the assumptions that the composite criterion (Y) has been regressed on the predictor (X) and the residuals ($Y_i - E[Y|X_i]$) have been computed and that the significance of the difference in mean residuals across the two groups have been tested by means of a t-test or a one-way ANOVA, the assumption of equal error variance across π_1 and π_2 is tested by testing the following null hypothesis:

$$H_{01}: \sigma^2[Y|X; \pi_1] = \sigma^2[Y|X; \pi_2]$$

$$H_{a1}: \sigma^2[Y|X; \pi_1] \neq \sigma^2[Y|X; \pi_2]$$

by calculating the following test statistic (assuming $S^2[Y|X; \pi_1] > S^2[Y|X; \pi_2]$:

$$F = S^2[Y|X; \pi_1]/S^2[Y|X; \pi_2]$$

$$F \sim F[n_{1-2}; n_{2-2}]$$

If H_{01} can not be rejected ($p>0.05$) the following saturated model is fitted on the data:

$$E[Y|X] = \alpha + \beta_1[X] + \beta_2[D] + \beta_3[X*D]$$

where $D = 0$ if group $= \pi_1$;

$D = 1$ if group $= \pi_2$;

The saturated model is then fitted by testing H_{02}:

$$H_{02}: \beta_2 = \beta_3 = 0|\beta_1 \neq 0$$

$$H_{a2}: \beta_2 \neq \beta_3 \neq 0|\beta_1 \neq 0$$

H_{02} is tested by calculating the following test statistic:

$$F = \{[SSR[b_1, b_2, b_3] - SSR[b_1]/[p - 1]\}/MSE[b_1, b_2, b_3]$$
$$F \sim F[p\text{-}1, n\text{-}p\text{-}1]$$

where p = 3 = the number of effects in the saturated model;

SSR = sum of squares regression; and

MSE = mean square error

If H_{02} cannot be rejected the saturated model reduces to the following equation:

$$E[Y|X] = \alpha + \beta_1[X]$$

If H_{02} cannot be rejected, it implies that the regression equations of groups π_1 and π_2 coincide, so that the use of the regression equation fitted on the combined group as the basis of the decision rule will be fair to members of both groups. If, however, H_{02} is rejected, it implies that the regression equations for groups π_1 and π_2 do not coincide but differ in terms of intercept and/or slope. The use of the combined equation to calculate E[Y|X] would thus result in unfair selection.

In order to establish whether the effect of group membership on criterion performance is dependent on the level of X or whether it is in fact responsible for a constant increment in Y independent of the level of X, the following null hypothesis is formulated and tested if H_{02} is rejected:

$$H_{03}: \ \beta_3 = 0|\beta_1 \neq 0; \beta_2 \neq 0$$
$$H_{a3}: \ \beta_3 \neq 0|\beta_1 \neq 0; \beta_2 \neq 0$$

H_{03} is tested by calculating the test statistic below:

$$F = \{[SSR[b_1, b_2, b_3] - SSR[b_1, b_2]/[p\text{-}2]\}/MSE[b_1, b_2, b_3]$$
$$F \sim F[p\text{-}2, n\text{-}p\text{-}1]$$

If H_{03} cannot be rejected, the interaction term is dropped from the saturated model so that the saturated model reduces to:

$$E[Y|X] = \alpha + \beta_1[X] + \beta_2[D]$$

so that:

$$E[Y|X;\pi_1] = \alpha + \beta_1[X]$$
$$E[Y|X;\pi_2] = [\alpha + \beta_2] + \beta_1[X]$$

If the above null hypothesis is rejected, it implies that the X*D interaction term explains significant additional Y variance in a model already possessing its main effects. Not rejecting H_{03} under the above conditions, however, implies parallel regression lines for $\pi 1$ and π_2 which differ in terms of intercept only. If H_{03} is not rejected, the hypothesis below could be tested:

$$H_{04}: \ \beta_2 = 0|\beta_1 \neq 0; \beta_3 = 0$$
$$H_{04}: \ \beta_2 \neq 0|\beta_1 \neq 0; \beta_3 = 0$$

If, however, H_{03} is rejected, the following null hypothesis is tested:

$$H_{05}: \ \beta_2 = 0|\beta_1 \neq 0; \beta_3 \neq 0$$
$$H_{05}: \ \beta_2 \neq 0|\beta_1 \neq 0; \beta_3 \neq 0$$

by calculating the test statistic below:

$$F = \{[SSR[b_1, b_2, b_3] - SSR[b_1, b_3]/[p\text{-}2]\}/MSE[b_1, b_2, b_3]$$
$$F \sim F[p\text{-}2, n\text{-}p\text{-}1]$$

If H_{05} can not be rejected, the group main effect should be dropped from the saturated model, thereby implying that the regression equations of π_1 and π_2 share a common intercept but differ in terms of slope:

$$E[Y|X] = \alpha + \beta_1[X] + \beta_3[X*D]$$

If H_{05} is rejected, the saturated model is retained, implying that the separate regression equations differ significantly in terms of intercept and slope. Thus:

$$E[Y|X] = \alpha + \beta_1[X] + \beta_2[D] + \beta_3[X*D]$$

so that:

$$E[Y|X;\pi_1] = \alpha + \beta_1[X]$$
$$E[Y|X;\pi_2] = [\alpha + \beta_2] + [\beta 1 + \beta_3][X]$$

The conditional probability for success and the expected criterion score should then be calculated for each applicant through the appropriate, best fitting, saturated or reduced regression model to ensure fair selection according to the Cleary model. If two or more predictors are used in the selection battery, the same basic procedure as above could be followed to test fairness in terms of the Cleary model. One possible method would be the replacement of the single predictor (X) in the saturated model with the linear combination of predictors $E[Y|X_i]$ and then to follow the test procedure above. Otherwise the saturated model must be expanded in terms of the number of predictor main effects and X*D interaction effects.

3.10.2 The Einhorn-Bass Fairness Model

The objective of the Einhorn-Bass model (1971) is not only to accept those individuals who are predicted to be above a certain minimum cut-off point on the criterion, but more specifically to be able to make the predictions within a specified (high) degree of confidence. Thus the probability of success, i.e. the probability with which the actual criterion score will fall above a specified criterion cut-off point, is emphasised in the Einhorn-Bass fairness model.

The criterion scores are predicted from a regression equation for subpopulations π_1 and π_2. If the predicted criterion values have different standard errors of estimate in the two different groups, it means that, although the test prediction of criterion performance may be the same for members of either group, the prediction for one group will involve a greater estimate of error than for the other group. The reason for this is the greater the standard error of estimate of a predicted score, the greater the possibility that the predicted criterion score will vary from the true criterion score. Thus, individuals A and B from groups π_1 and π_2 respectively may have the same predicted criterion score but, because one group may have a smaller standard error of estimate, the one predicted criterion score may have less risk of error associated with it.

It is evident from the above that the standard error of estimate has significance in the equal risk fairness model. Einhorn and Bass (1971, p.264) in addition mention two reasons of importance for the standard error estimate:

> The test-criterion correlation coefficient, which is an index of accuracy of prediction of standardised scores is less meaningful than the error of estimate, which is expressed in raw-score terms.
>
> In fact, we would further argue that in terms of the issue of test discrimination, it is *primarily* differences between different groups in standard errors of estimate, *rather than* differences in test-criterion correlations, which will be of most relevance (Einhorn & Bass, 1971, p.264-265).

The Einhorn-Bass model specifies that applicants from different subpopulations with the same probability to succeed (conversely risk) must have the same probability of selection (hence equal risk model) (Holburn, 1991; Petersen & Novick, 1976). The risk of falling below the criterion cut-off point can be calculated. The standard error of estimate of the conditional criterion distributions may, however, differ between the two groups, which means that the level of risk associated with a specific (composite) predictor score may be different for members of different groups who have the same score. To ignore this and to grant applicants from the subpopulations equal chances of selection would then be considered unfair by the Einhorn-Bass model. Applicants with a risk greater than the chosen maximum will be rejected, whereas those individuals with the smallest risk are selected first.

To illustrate, Figure 3.11 (a) shows the relationship between a predictor variable (test) and a criterion variable for one subpopulation in which the conditional distribution of the criterion (Y) given the predictor (X) is assumed to be normal. The risk level for a particular value x on the test is represented by the part of the curve below y* on x*.

Although the regression lines in Figure 3.11 (b) are the same, the standard errors of estimates differ. The standard error of estimate for subpopulation π_1 is smaller that for π_2. Thus, the level of risk associated with any test score x is less for members of subpopulation π_1 than for members of subpopulation π_2. Thus, as Petersen and Novick (1976) explain, if all applicants with predicted criterion scores greater or equal to y* were to be considered for selection, the selection procedure would discriminate against subpopulation π_1.

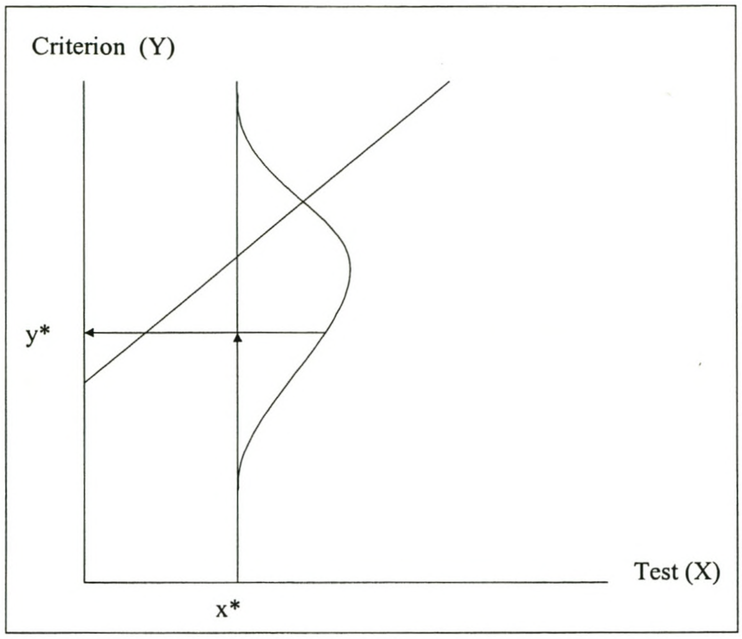

Figure 3.11 (a) Conditional distribution of criterion on test showing risk level

(Peterson & Novick, 1976, p.20)

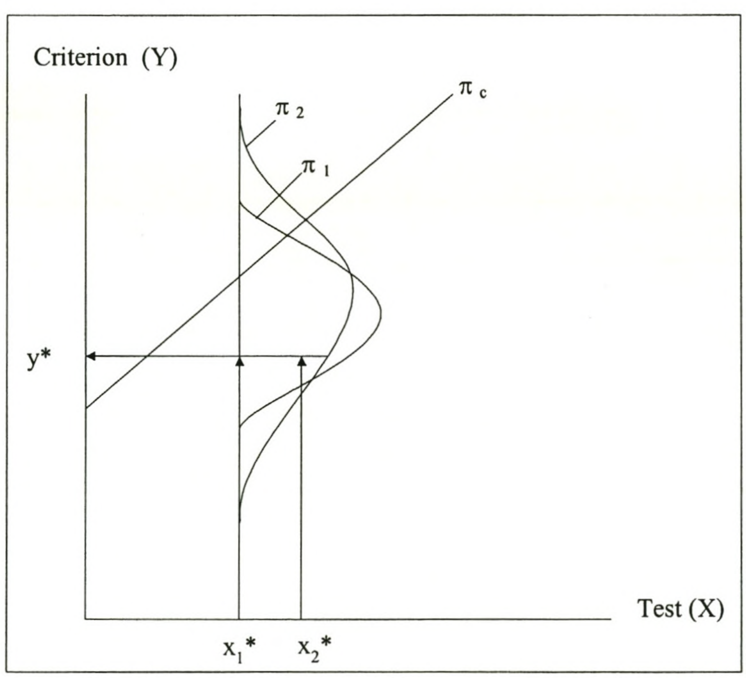

Figure 3.11 (b) Subpopulations with common regression line but different standard errors of estimate

(Peterson & Novick, 1976, p.20)

As is evident from Figure 3.11 (b) the risk that persons from subpopulation π_1 with test scores equal to x^*_1 will fail will be equal to the risk that persons from subpopulation π_2 with test scores equal to x^*_2 will fail. Members of the two subpopulations should, therefore, not be afforded the same chances of selection, even though their expected criterion performances coincide.

In Figure 3.11 (c) below the intercepts differ for π_1 and π_2, though the standard error of estimates and the slopes are the same. When regression slopes are assumed equal for the two groups and the standard error of estimates are equal, the equal risk model reduces to the regression or Cleary model. However, the illustration in Figure 3.11 (c) represents the following: (a) for any test score x the level of risk is less for a member of π_2 than for a person from π_1, and (b) the test would discriminate against members of subpopulation π_2 if a single cut-off point were to be used (or, more generally, if members of π_1 and π_2 with the same expected criterion score would be treated equally in selection. The equal risk model would consider it fair if member of π_1, with test scores equal or greater than x*, were to be accepted (Petersen & Novick, 1976) (see Figure 3.11 (c)).

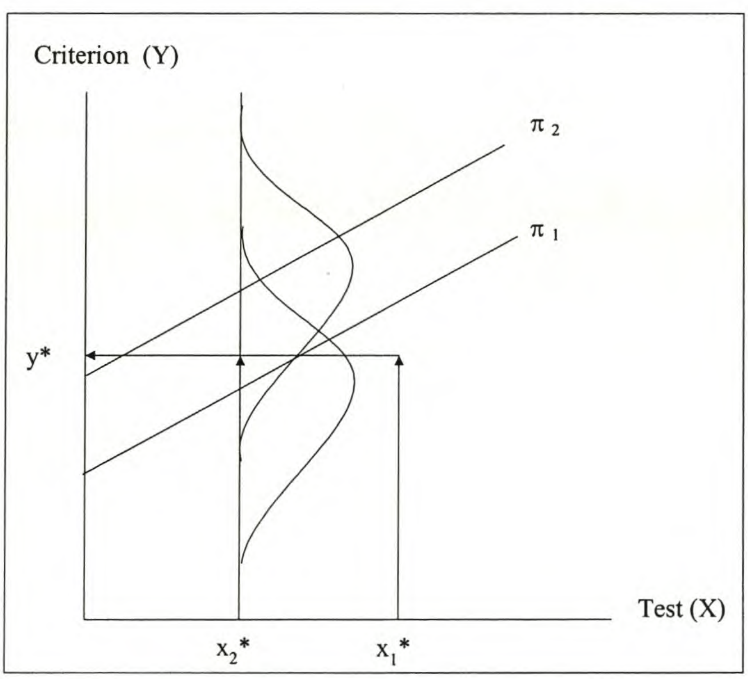

Figure 3.11 (c) Subpopulations with the same standard error of estimate and the same slope but different intercepts

(Peterson & Novick, 1976, p.20)

To statistically analyse the fairness of a selection procedure in terms of the Einhorn-Bass model, the following steps are required:

Again assume two groups π_1 and π_2 and a linear regression of a (composite) criterion on a single predictor or a weighted linear combination of predictors. The assumption of equal error variances across π_1 and π_2 is tested by testing the following null hypothesis:

$$H_{01}: \sigma^2[Y|X; \pi_1] = \sigma^2[Y|X; \pi_2]$$
$$H_{a1}: \sigma^2[Y|X; \pi_1] \neq \sigma^2[Y|X; \pi_2]$$

H_{01} is tested by calculating the test statistic below:

$$F = S^2[Y|X; \pi_1]/S^2[Y|X; \pi_2]$$
$$F \sim F[n_{1\text{-}2}; n_{2\text{-}2}]$$
$$= MSE_1/MSE_2$$
$$\sim F[n_{1\text{-}2}; n_{2\text{-}2}]$$

If H_{01} is not rejected, and the use of a single regression line is fair according to Cleary (1968), selection based on the conditional probability of success (or failure) derived from the single regression equation and the pooled estimate of the standard deviation of the conditional criterion distribution (assuming homoscedasticity) would be considered fair. In addition, if X would constitute a single predictor or a (linear) combination of predictors, a single critical score X_k can be derived such that $P[Y<Y_k|X_k] = \delta$, where δ constitutes the maximum probability of failure the decision-maker is prepared to tolerate. Given δ, Z is read off from the standardised normal probability table. E[Y|X] and X_k are then calculated such that $P(Y<Y_k|E[Y|X]) = \delta$:

$$-Z = \{Y_k - E[Y|X]\}/S[Y|X]$$
$$-ZS[Y|X] = Yk - E[Y|X]$$
$$E[Y|X] = ZS[Y|X] + Y_k$$

where S[Y|X] is the root mean square error (MSE) for the joint regression line.
Calculate X_k so that $P[Y<Y_k|X=X_k] = \delta$:

$$E[Y|X] = a + b[X]$$
$$X_k = (E[Y|X] - a)/b$$
$$P[Y<Y_k|X=X_k] = \delta$$

If H_{01} cannot be rejected, but the use of a common regression line is unfair according to Cleary, selection based on the conditional probability of success (or failure) would be considered fair by the equal risk model only if it is derived from the appropriate multiple regression model and the pooled estimate of the standard error of estimate. Different/separate critical cut-off scores would, however, now have to be estimated, given a chosen measurement risk level δ. The standard score Z is again read off, given δ. The common root MSE is then calculated:

$$S^2[Y|X; \pi_p] = [(n_{1-2})S^2[Y|X; \pi_1] + [n_{2-2}]S^2[Y|X; \pi_2]/[n_1 + n_{2-4}]$$
$$= [SSE_1 + SSE_2]/[n_1 + n_{2-4}]$$
$$S[Y|X; \pi_p] = \sqrt{S^2[Y|X; \pi_p]}$$

Calcultate E[Y|X] so that $P(Y<Yk|E[Y|X]) = \delta$:

$$-Z = \{Y_k - E[Y|X]\}/S[Y|X; \pi_p]$$
$$-ZS[Y|X; \pi_p] = Y_k - E[Y|X]$$
$$E[Y|X] = ZS[Y|X; \pi_p] + Y_k$$

where $S[Y|X; \pi_p]$ is the root MSE for the separate regression lines. Next, X_k should be calculated for each group separately so that $P[Y<Y_k|X=X_k] = \delta$:

$$E[Y|X]=a + b_1[X] + b_2[D] + b_3[D*X]$$

For D = 0 the equation reads:

$$E[Y|X; \pi_1] = a + b_1[X]$$
$$X_{k1} = (E[Y|X; \pi_1] - a)/b_1$$

For D = 1 the equation reads:

$$E[Y|X; \pi_2]=[a + b_2] + [b_1 + b_3]X$$

$$X_{k2} = (E[Y|X; \pi_2] - [a + b_2])/[b_1 + b_3]$$

$$P[Y<Y_k|X=X_{k1}] = P[Y<Y_k|X=X_{k2}] = \delta$$

If H_{01} is rejected and the use of a common regression line is fair according to Cleary (1968), selection based on the conditional probability of success (or failure) would be considered fair by the equal risk model only if it would be derived from the common regression equation by utilising each group's unique estimate of the standard deviation of the conditional criterion distribution (again assuming homoscedasticity). Different/separate critical criterion cut-off scores would again have to be calculated given a chosen maximum risk level δ. The standard score Z is again read off from the standard normal probability table, given δ. $E[Y|X; \pi_2]$ is consequently calculated where:

$$E[Y|X; \pi_1] = Z_1S[Y|X; \pi_1] + Y_k$$

and

$$E[Y|X; \pi_2]=Z_2S[Y|X; \pi_2] + Y_k$$

where $Z_1 = Z_2$, so that $P(Y<Y_k|E[Y|X]) = \delta$.

X_k is then calculated so that $P[Y<Y_k|X=X_k] = \delta$:

$$X_{k1} = ([E[Y|X; \pi_1] - a)/b$$

$$X_{k2} = ([E[Y|X; \pi_2] - a)/b$$

so that:

$$P[Y<Y_k|X=X_{k1}] = P[Y<Y_k|X=X_{k2}] = \delta$$

If H_{01} can be rejected and the use of a common regression line is unfair according to Cleary, selection based on the conditional probability of success (or failure) would be considered fair by the equal risk model only if calculated via the appropriate multiple regression equation and utilising each group's unique standard error of estimate. A separate critical cut-off score will again have to be calculated given a chosen maximum risk level δ. The standard score Z is again read off from the standardised normal probability table, given δ. $E[Y|X; \pi_i]$is subsequently calculated such that $P(Y<Y_k|E[Y|X; \pi_i]) = \delta$ by calculating:

$$E[Y|X; \pi_1] = Z_1S[Y|X; \pi_1] + Y_k$$

$$E[Y|X; \pi_2] = Z_2S[Y|X; \pi_2] + Y_k$$

where $Z_1 = Z_2$

Subsequently X_k is computed so that $P[Y<Y_k|X=X_k] = \delta$:

$$E[Y|X] = a + b_1[X] + b_2[D] + b_3[D*X]$$

For D = 0:

$$E[Y|X; \pi_1] = a + b_1[X]$$

$$X_{k1}=(E[Y|X; \pi_2]-a)/b_1$$

For D = 1:

$$E[Y|X; \pi_2] = [a + b_2] + [b_1 + b_3]X$$

$$X_{k2} = (E[Y|X; \pi2] - [a + b_2])/[b_1 + b_3]$$

$$P[Y<Y_k|X=X_{k1}] = P[Y<Y_k|X=X_{k2}] = \delta$$

3.11 DEVELOPMENT OF A CHECKLIST

The psychometric audit aims at establishing the scientific rationality of the methodology through which the selection procedure was developed and justified. The audit essentially compares the way in which the selection procedure has actually been developed and justified with the ideal procedure derived from the Guidelines (Society of Industrial Psychology, 1998) and existing psychometric literature. Furthermore, the purpose of periodic psychometric audits is to point out the degree of adherence of the selection procedure to current legislation and the Guidelines (Society of Industrial Psychology, 1998), and therefore to identify substantial and procedural shortcomings in the design and justification of the selection procedure. Therefore, the actual Call Centre selection procedure and its developmental history, and the ideal approach to the development and justification of a selection procedure would be examined step by step.

A checklist has been developed that represents a theoretical ideal, an operational gauge, entailing the most significant facets of the validation process according to which any personnel assessment procedure must be validated. The items in the checklist refer to the critical behaviours that must be executed when validating a selection procedure so as to ensure a valid and credible verdict on the relevance, utility and the fairness of the selection procedure. Its use thus lies therein, that it enables one to tick off, as it were, the critical behaviours that have, or have not, been executed in the validation of a selection procedure which would ensure a valid and credible verdict on the relevance, utility and fairness of the selection procedure. The checklist would thus be used to summarise the extent to which the actual selection procedure conforms to the ideal procedure as set out in the Guidelines (1998).

Such a checklist has been developed for the purpose of this study. To overcome repetition, the identified critical behaviours set out in the form of a checklist feature only in Chapter VI, Table 6.1. It should be noted, however, that the checklist in Chapter VI represents an evaluation of the existing Call Centre selection procedure. That is, substantial and procedural shortcomings in the existing design and justification of the selection procedure have already been identified. The items that have, or have not, been executed in the validation of the current selection procedure, have been ticked off, as it were.

CHAPTER IV

A SYSTEMATIC DESCRIPTION OF THE CALL CENTRE SELECTION PROCEDURE

4.1. THE CALL CENTRE

A Call Centre is a telephonic answering service. The service rendered by its employees is one where relevant information, as it is received telephonically from the company's clients, is handled, transacted and transferred appropriately. The information the Call Centre staff receive is to be handled effectively and efficiently, with special emphasis on professionalism, accuracy and speed.

The Call Centre of the South African company under consideration was developed by a multi-disciplinary team of company experts and has been implemented systematically from 1 September 1998. An assessment procedure for the selection of Call Centre staff was developed and implemented by The Company with the help of an external consultant. The selection procedure is still undergoing changes and systematic improvements in the structure, and partly in the operation, of the Call Centre in a quest to arrive at a well-documented, valid and reliable selection procedure that can be confidently used for the selection of Call Centre staff in future in accordance with current legislation.

The Company has two Call Centres in South Africa. The first Call Centre was established in the Western Cape (Call Centre South), and one was later made operational in the Gauteng area (Call Centre North) due to increasing client servicing demands and resultant operational costs.

The rationale behind the Call Centre is that a shift was to be made in conjunction with the current world-wide trend away from the typical physically located offices to a telephonic client-servicing and policy-processing system in order primarily to save the increasing costs incurred by operating offices.

The value of The Company's Call Centre lies therein, that The Company can communicate telephonically with clients directly and efficiently in dealing with anything from general enquiries to more technical transactions. The efficiency of the Call Centre is primarily due to the well-trained, broad-skilled key role-players in the Call Centre, namely the Client Service Representative, the Process Assistant/Functional Specialist and the Coach who work in a hierarchical relation to one another in what could be defined as an information processing hierarchy.

The Client Service Representative, the first point of contact, routes accurate details of the needs or problems of the clients to the Process Assistant or the Coach, if he/she is not able to offer a one-stop service. The Process Assistant delivers a comprehensive administrative service to specific clients who contact them or are relayed to them. The Functional Specialist processes complex, specific and exceptional cases of specific clients who contact them or are relayed to them. The Coach is responsible for the management of a team consisting of Client Service Representatives and Process Assistants, the efficient utilisation of the processes, and the creation of a climate where client service and problem solving are valued and rewarded.

The importance of the Call Centre, in terms of its organisational function, lies in its potential and invaluable contribution to organisational effectiveness, efficiency and customer care and satisfaction, as the Call Centre is more often than not the first line of contact clients have with The Company. Understanding the significance of the Call Centre from the perspective of the organisational structure, its function and its contribution to the company allows one a greater understanding of the significance of the present study that researched the manner in which such Call Centre staff are being selected.

4.2 JOB ANALYSIS

With the shift from the traditional system of telephonic answering services to the new Call Centre system, a new process-based competency identification approach to job analysis in The Company was utilised. The process-based methodology of job analysis refers to a description of the work process, i.e. it necessitates a description of what the work entails, with the focus on both work behaviours and work output.

A multi-disciplinary team from within The Company developed a description of the work process by firstly deciding on the purpose of each key role-player (that is, the Client Service Representative, the Process Assistant/Specialist and the Coach) of the Call Centre in The Company and, secondly, by deciding on the context within which each key role-player should function on a day to day basis.

The key role-player can, for example, be described as a person who should process and solve complex, unique and exceptional problem cases experienced by The Company's specific (defined) clients. The context refers to a very general and broad description of the job, such as the requirement of international client service standards, the "really" professional interaction with the client that satisfies customer intimacy needs, or the acquisition of knowledge that should become critical to each person.

From the context specific outputs, which each key role-player is expected to demonstrate, are defined. Examples of outputs are: updating client information, complaint resolution and identifying client needs and problems. The work output information (also known as knowledge areas) has been used for the development of competencies for each key role-player functioning within the Call Centre. The competencies have been developed according to the competency identification methodology, more specifically the flexible job competency model method (McLagan, 1990; Dubois, 1993) and the critical event method (Dubois, 1993). Both are based on McClelland's work, which resulted in the creation of a research process called the Job Competence Assessment Method (JCAM) (McClelland, 1973; 1976).

A feature of the flexible job competency model method is the identification and use of future assumptions about the organisation and the job. The use of this method results in the availability of job roles, job outputs, quality standards for the outputs, and behavioural indicators for each job competency (Dubois, 1993). McLagan (Dubois, 1993, p.100) identifies the following steps for the completion of the flexible job competency model method:

- Assemble and review all available information that is pertinent to the job;
- Identify an expert panel to help in the process;
- Develop present and future assumptions about the job in the context of the organisation;
- Develop a job outputs menu, including (optional) quality criteria for each output;
- Construct a job competencies menu and the behavioural indicators for each competency;
- Determine a menu of job roles through a cluster analysis of the job outputs;
- Construct one or more generic job competency models; and
- Brief the client or client group on the project results.

Each member of the multi-disciplinary team identified the generic competencies he/she thought most relevant for the three positions in question. By a process of elimination and agreement, the ten most important competencies were selected. The identified competencies for the Client Service Representative, the Process Assistant and the Coach, in no particular order, are as following:

- Identifying and solving problems;
- Eagerness to learn;
- Handling information;
- Client service orientation;
- Communication;
- Interpersonal sensitivity;
- Co-operation;
- Performance orientation;
- Perseverance;
- Self-control;
- Analysis;
- Decision-making;
- Achievement orientation;
- Decisiveness and execution;
- Developing and empowering others;
- Teamwork; and
- Objective setting and management control.

From the identified and defined competencies, related behavioural indicators have been developed. It has been specified that the behavioural indicators have been developed from an understanding of the job as well as from previous experience of other, similar jobs. The behavioural indicators represent the developed and defined competencies in behavioural, observable terms. For example, the concurrent behavioural indicators of a competency that is defined as "identifying and solving problems" could include the interpretation of a client's questions, the gathering of all required information, and/or the in-depth investigation of the problem.

It should be mentioned that a formal job analysis has, until this stage, never been executed, as it was the first time the key role-players' function within a given context was described. The actual activity of describing the context within which the individual key role-players are to function has, however, not been defined as a job design; rather it is said that a formal job description (so-called job profiling) would automatically follow from a description of the incumbent and the context within which he/she would function.

4.3 PREDICTOR VARIABLES

4.3.1 Introduction

The assessment instruments used for the selection of the Client Service Representative, the Process Assistant and the Coach have been set out below. The psychometric tests that were used for the selection of Call Centre staff were all products of Saville & Holdsworth Ltd (SHL). It has been reported that the rationale behind the use of these products from the perspective of the external consultant is that she was supportive of SHL's products at the time of the selection of Call Centre staff; the rationale is reflected in the products' justification as "job-related instrumentation". The case study and the role play for each of the three groups was developed by the external consultant. The Call Centre staff were selected on the basis of their performance on psychometric tests, case studies and role play. The simulation exercises were weighted the heaviest in the importance of their contribution to the prediction of future job performance.

The selection procedure was originally developed as a two-phase selection procedure for the Client Service Representative, the PA/Specialist and the Coach. The rationale behind such a two-phase selection procedure was that everybody that had progressed through to the second phase would be given the opportunity to apply for a different category or a different position altogether. The two-phase approach would make it easier for decision-makers to compare the applicants for the different categories or positions in terms of their performance on the selection tests. However, due to certain (unknown) practical considerations, the only two categories that were guided through a two-phase selection procedure were the Client Service Representative and the Coach.

4.3.2 Client Service Representative

The assessment of the Client Service Representative (CSR) proceeds in two phases. Phase one involves a case study and psychometric testing, whereas the second phase (if the applicant is short-listed after the first phase) is role play. The first assessment takes on average four hours; the second an hour.

The assessment instruments used, and the competencies assessed in the selection of the Client Service Representative, have been set out below.

❖ Case study

The following 4 variables are measured:

- Identifying and solving problems;
- Handling information;
- Performance orientation; and
- Perseverance.

❖ Psychometric testing: Client Contact Styles Questionnaire (CCSQ)

The following 10 variables are measured:

- Identifying and solving problems;
- Eagerness to learn;
- Handling information;
- Client Service orientation;
- Communication;
- Interpersonal sensitivity;
- Co-operation;
- Performance orientation;
- Perseverance; and
- Self-control.

❖ Psychometric testing: Customer Contact Aptitude Series (CCAS) (Client Contact: Verbal Interpretation; Client Contact: Numerical Interpretation)

The following 2 variables are measured:

- Verbal interpretation: identifying and solving problems; and

- Numerical interpretation: identifying and solving problems.

❖ Psychometric testing: Personnel Test Battery (PTB) (Clerical Abilities: Verbal Usage; Clerical Abilities: Classification; Clerical Abilities: Clerical Checking)

The following 3 variables are measured:

- Verbal usage: handling information;
- Classification: handling information; and
- Clerical checking: handling information.

❖ Role play

The following 6 variables are measured:

- Identifying and solving problems;
- Client service orientation;
- Communication;
- Interpersonal sensitivity;
- Performance orientation; and
- Self-control.

4.3.3 Process Assistant/Specialist

The assessment of the Process Assistant (PA)/Specialist proceeds in one phase. Phase one involves a case study and psychometric testing. The assessment takes on average four hours for phase one.

The assessment instruments used, and the competencies assessed in the selection of the Process Assistant/Specialist, have been set out below.

❖ Case study

The following 4 variables are measured:

- Identifying and solving problems;
- Client service orientation;

- Performance orientation; and
- Perseverance.

❖ Psychometric testing: Client Contact Styles Questionnaire (CCSQ)

The following 10 variables are measured:

- Identifying and solving problems;
- Eagerness to learn;
- Handling information;
- Client service orientation;
- Communication;
- Interpersonal sensitivity;
- Co-operation;
- Performance orientation;
- Perseverance; and
- Self-control.

❖ Psychometric testing: Customer Contact Aptitude Series (CCAS) (Client Contact: Verbal Interpretation; Client Contact: Numerical Interpretation)

The following 2 variables are measured:

- Verbal interpretation: identifying and solving problems; and
- Numerical interpretation: identifying and solving problems.

❖ Psychometric testing: Personnel Test Battery (PTB) (Clerical Abilities: Verbal Usage; Clerical Abilities: Classification; Clerical Abilities: Clerical Checking)

The following 3 variables are measured:

- Verbal usage: handling information;
- Classification: handling information; and
- Clerical checking: handling information.

4.3.4 Coach

The assessment of the Coach proceeds in two phases. Phase one involves a case study and psychometric testing. Phase two (if an applicant is short-listed after the first phase) is a role play. The assessment takes on average two and a half hours for the first phase; an hour for the second phase.

The assessment instruments used, and the competencies assessed in the selection of the Coach, have been set out below.

- ❖ Case study

  The following 2 variables are measured:

  - Analysis; and
  - Decision-making.

- ❖ Psychometric testing: Occupational Personality Questionnaire (OPQ)

  The following 9 variables are measured:

  - Analysis;
  - Decision-making;
  - Client service orientation;
  - Achievement orientation;
  - Decisiveness and execution;
  - Developing and empowering others;
  - Teamwork;
  - Interpersonal sensitivity; and
  - Objective setting and management control.

- ❖ Psychometric testing: Critical Reasoning Test Battery
  - Verbal evaluation; and
  - Interpreting data

❖ Role Play

The following 7 variables are measured:

- Analysis;
- Client service orientation;
- Achievement orientation;
- Decisiveness and execution;
- Developing and empowering others;
- Interpersonal sensitivity; and
- Objective setting and management control.

4.4 VALIDATION SAMPLE

The selection of a validation sample and obtaining relevant predictor and criterion information from its members is, as such, not part of The Company's selection strategy. It is, however, necessitated to justify the selection procedure by simulating it on the validation sample. The importance of the sample lies therein, that it is the group on which the justification of the selection procedure is based. It is from results obtained on that group that decisions on the efficiency and equity of the selection procedure will be taken. The intention is to generalise the research results obtained to the overall applicant population.

As was mentioned earlier, two physical Call Centres (North and South) exist, but only one virtual Call Centre was used for the purpose of the validation study. Therefore, the sample information for Call Centres North and South was combined. Although the data from both the Call Centres are treated equally for the purposes of the statistical analyses, the description of the Call Centre selection procedure proceeds from the perspective of the South Call Centre. The combination of sample data can be justified in terms of the mode of operation of the Call Centre and the size of the sample.

By mode of operation is meant the manner in which the centrally located switchboard diverts incoming calls to the appropriate Call Centre operator located in the area from which the call was made. Therefore, Call Centres North and South cannot be distinguished in terms of their services (operation), but only in terms of their location. Thus, the two existing, physical Call Centres can be combined into one virtual Call Centre for the purposes of the study.

Combining the two Call Centres thus increases the size of the sample and therefore enables greater effectiveness and accuracy (in terms of possible future generalisations) of the statistical analyses to be made. The results obtained from statistical analyses of larger samples would allow for more accurate generalisations and inferences to be made about the population from the sample. The sample population has been defined as consisting of those individuals who have been employed into the three respective categories of CSR, PA/Specialist and Coach.

The subjects (job incumbents) of the validation study are all the candidates that had been employed as operatives (either as CSR, PA/Specialist or Coach) and that have been operational for at least six months in either one of the three respective job categories. The criterion of six months was decided upon to allow the employees to complete their initial training and to settle into their jobs. The sample was drawn in January/February 2000 as, due to high, monthly employee turnover, it was the only stage that was relatively stable in terms of employees having worked at the Call Centre for a minimum of six months.

The composition of the combined validation sample in terms of race by position looks as follows (Table 4.1):

Table 4.1 Frequency table of sample: position by race

POSITION ↓	RACE Asian	Black	Coloured	White	TOTAL
Coach	0 0.00%	1 0.31%	2 0.62%	38 11.84%	41 12.77%
CSR	2 0.62%	6 1.87%	36 11.21%	98 30.53%	142 44.24%
PA	3 0.93%	9 2.80%	30 9.35%	96 29.91%	138 42.99%
Total	5 1.56%	16 4.98%	68 21.18%	232 72.27%	321 100.00%

Note: Frequency Missing = 7

The composition of the combined validation sample in terms of gender by position looks as follows (Table 4.2):

Table 4.2 Frequency table of sample: gender by position

POSITION ↓	GENDER Female	Male	TOTAL
Coach	34 10.37%	7 2.13%	41 12.50%
CSR	109 33.23%	38 11.59%	147 44.82%
PA	108 32.93%	32 9.76%	140 42.68%
Total	251 76.25%	77 23.48%	328 100.00%

4.5 CRITERION VARIABLES

The job performance of the three key role players (CSR, PA/Specialist, Coach) was measured via two separate techniques. Firstly, job performance was measured in terms of the score received on a behavioural observation scale questionnaire and, secondly, job performance was measured in terms of an incentive received.

4.5.1 Criterion Questionnaire

The Company, together with the (first) external consultant, developed behavioural observation scale questionnaires for each of the key role-players. The development of the questionnaires was aimed at measuring each of the competencies, as defined by the job analysis, for each type of role-player. In other words, the questionnaires were aimed at evaluating the behaviour of the CSR, PA/Specialist and the Coach, respectively.

The questionnaire for the Coaches consisted of 127 items, and the immediate subordinates of the Coach completed the questionnaire. The questionnaire for the CSRs consisted of 98 items, and the

Coach of each employee completed the questionnaire. A 78-item questionnaire was developed for the PA/Specialists. The Coach of each employee completed the questionnaire.

Qualitative, behavioural aspects of the employee were measured with each of the job performance questionnaires. The questionnaires were originally designed to measure the full spectrum of employees' elicited positive and negative behaviour. The questionnaires have, however, been adapted to measure only elicited positive employee behaviour.

4.5.2 Performance Incentive

Job performance was also measured in terms of a monetary incentive. The incentive is an index, based on commission received as a result of the output achieved as measured by the job performance evaluation system. The job performance measure obtained for the respective employees was originally obtained and measured via the performance appraisal system. The emphasis of performance measurement in the Call Centre is strictly on operational, IT-calculated output. The output clearly defines the minimum requirements set. Examples are the number of telephone calls answered, the time in which a request/complaint is managed, and the profit made. Only quantitative output is measured with the performance appraisal technique.

The commission received by the employees in January/February 2000 was used as, for all practical purposes, it was during these two months that the sample was drawn based on a minimum requirement of having worked in the Call Centre for at least six months. It was during these two months that the usually high employee turnover rate was at its most stable.

The maximum possible achievable incentive differed across the categories of CSR, PA/Specialist and Coach. The PAs were divided into groups PA1 and PA2, where each of these two groups would be eligible to receive a different maximum incentive depending on which group the employee was allocated to. The rationale behind such a differentiation - in fact, the criteria for the allocation into PA1 or PA2 - is unknown.

It has been reported that the amount of commission received can be dependent on situational factors over and above the performance of the individual. That is, the individual incentives can be adapted according to the amount of money The Company has available for the allocation of incentives. If there is insufficient money available with which to pay the deserved individual incentives, an average incentive amount would be calculated and allocated to the relevant parties.

The Company developed a formula for the calculation of the incentives of both the North and South Call Centre employees:

(True incentive ÷ Maximum incentive) × 0.3 (0.325 in the case of PA1)[1] = %

However, judging from the original information received, the North and South Call Centre employees were treated differently in terms of the calculation of the formula. It was thought that the original incentives per employee were either calculated in terms of an overall 30% or a 100% in terms of the maximum incentive the employee would be eligible to receive depending on which category the employee belonged to. However, when the incentives were re-calculated to re-check the figures, it was found that the above formula decreased the incentives for the South sample by 30%. The incentives had thus been calculated differently for the two physical Call Centres, and the information received was inconsistent. The original formula, with which the incentives for the North and South Call Centres were originally calculated, was thus subsequently changed and re-calculated in terms of:

Incentive eligible to receive per month depending on group membership ÷ Basic salary received per category = % actual incentive received

4.5.3 Psychometric analyses

No statistical, psychometric analyses had been performed on any of the data of the validation sample by The Company by the time this psychometric audit started. The Company has, in the meantime, outsourced the performance of the statistical analyses of the validation group to a (second) external consultant.

[1] It has not been reported exactly what the 0.325 is representative of nor what it was derived from.

CHAPTER V

AN EVALUATION OF THE CURRENT SELECTION PROCEDURE

5.1 INTRODUCTION

The importance of the checklist set out in Chapter VI is twofold. Firstly, the checklist represents the theoretical ideal in terms of the validation process required to justify a selection procedure. Secondly, it functions as a framework guiding the evaluation of the current selection procedure. The validity of the methodological procedure used in the development and validation of the existing Call Centre selection procedure can thus be evaluated in terms of the eleven sets of activities set out in the checklist. The evaluation thus entails an overall description of the activities that have been executed by The Company (as well as activities that have not been executed) in their effort to establish a valid, credible and fair selection procedure. It also entails the identification of substantive and/or procedural shortcomings of the current selection procedure as brought to the attention by the checklist.

5.2 JOB ANALYSIS

The job analysis seems to have proceeded successfully. The job analysis was performed systematically and thoroughly and was administered on a valid and representative sample. A formal job description has been compiled and documented.

The job analysis technique utilised is reasonably well known and well documented in the literature (e.g. Dubois, 1993; McClelland, 1973,1976; McLagan, 1990). The Company, however, did not compile a formal, written description on how exactly it conducted the job analysis. From the information obtained for the purposes of the study, it is evident that great effort was made to comply with the directives of the flexible job competency model method as set out in Dubois (1993). Nonetheless, the Author still experiences a slight sense of uneasiness about the detail and/or exactness with which the procedures advocated by McLagan (Dubois, 1993) was followed.

5.3 PREDICTOR DEVELOPMENT

It is difficult to ascertain the degree to which the selection procedure has been based on a scientifically credible performance theory. A necessary but not sufficient prerequisite for efficient and equitable human resource selection (under a construct-oriented approach) is the ability to explain differences in criterion performance in terms of differences in employee characteristics.

Two issues are therefore important, namely the identity of predictor constructs affecting criterion performance, and the nature of the effect of the various predictor constructs on criterion performance (i.e. positive, negative, linear or curvilinear). Efficient selection is possible if the factors that affect performance and the manner in which they affect performance are understood.

The most fundamental manner in which the efficiency of selection procedures can be improved is thus to expand and improve the performance hypothesis through the inclusion of additional relevant predictor constructs and through alterations to statements on the nature of the relationships between predictor and criterion constructs. This, however, presupposes that the performance hypothesis has been developed and documented formally and explicitly. This does not seem to be the case with the current Call Centre selection procedure.

The choice of predictors for the Call Centre selection procedure, and the manner in which the information was combined to arrive at a selection decision, imply at least a rudimentary performance hypothesis. The implicit nature of the performance hypothesis makes it unlikely that predictor constructs would have been constitutively defined prior to operationalisation.

The psychometric tests that were used as predictors for the selection of the Call Centre staff of the CSR, PA/Specialist and Coach were obtained from the psychometric test developing and publishing company, Saville & Holdsworth, Ltd (SHL), whose products are well standardised. SHL is well known world wide for their expertise and (quantitative) research regarding the validity and reliability of psychometric tests. Empirical evidence thus exists for the support of the specific predictors used in the Call Centre selection procedure in terms of their factorial/construct validity and reliability through previous research conducted. Whether these predictor measures have also been examined for differential item functioning or item bias, however, is not clear.

Reasonable psychometric evidence seems to exist to support the claim that the psychometric tests utilised in the Call Centre selection procedure do measure those predictor constructs contained in the implicit performance hypothesis they intended to measure. The predictors were chosen on the basis of the (first) external consultant's experience with SHL tests and previous experience in the selection of Call Centre staff in a similar environment with similar competencies.

The case study and the role play were developed by the external consultant. Neither the case study nor the role play had been validated prior to their use. The case study and role play were developed and chosen to assess a common set of constructs. Whether the different assessment techniques (case study, role play and psychometric tests) designed to measure a specific construct do in fact measure the same construct is open to question.

What is also questionable is the manner in which the observed behaviour has been rated. No concrete information is readily available as to how the elicited candidate behaviour has been judged. Judging by the 5-point scale that was available for the judges to rate the elicited successful/unsuccessful behaviour, it is strongly suspected that the subjective opinion of the judges determined the allocation of points on the 5-point scale. The objectivity of the case study and role play assessment thus seem somewhat suspect. The extent to which the case study and role play assessment procedures have been standardised is not clear. No manuals seem to exist for these procedures.

5.4 CRITERION DEVELOPMENT

A prerequisite for the development of a scientifically credible performance theory is the explicit conceptualisation of the multi-dimensional criterion construct, work success. No formal constitutive definition of the final criterion seems to have been developed. This must necessarily impede the development of a performance hypothesis, and it complicates the development of operational criterion measures. The explanation and measurement of a construct must necessarily be problematic if one cannot obtain a firm intellectual grasp on the construct.

Nonetheless, operational criterion measures have been developed to assess the criterion construct. Although a connotative interpretation is thus implicitly implied, the absence of a formal, explicit constitutive definition has serious implications for the psychometric justification of the operational criterion measures.

In the absence of a formal, constitutive definition that explicates the internal structure of the criterion construct and its relationship to the outcomes implied by the objectives of the Call Centre, the psychometric evaluation of the operational criterion measures become difficult. It is almost impossible to decide whether a construct is measured comprehensively if vagueness exists on what exactly is being measured.

No evidence exists to suggest that the operational criterion measures have been qualitatively evaluated in terms of criterion contamination, relevance, deficiency or reliability.

Moreover, it is important to note that the criterion questionnaire has been adapted from its original structure by The Company without prior consultation with the external consultant. Sections were changed, omitted and replaced. The questionnaire, in the form that it was originally developed and in the revised form in which it is to be used for the validation of the Call Centre selection procedure, has never been psychometrically evaluated. The questionnaire has not been item analysed empirically, nor has it been examined empirically for differential items functioning. The reliability or the factorial or construct validity of the criterion measures have also never been determined. As a result, no evidence exists that the performance measurements do in fact provide reliable and valid measures of the criterion construct.

This in turn means that, even if it could be shown that the predictors comprising the selection procedures do correlate significantly with the operational criterion measures, it would still constitute insufficient evidence to fully justify the use of the predictors for the selection of Call Centre personnel. The existence of significant correlations between predictors and an operational criterion measure would necessarily imply the possibility of predicting the operationalised criterion conditional on the predictor score achieved. However, this would not necessarily imply a concomitant ability to rank order individuals in terms of their standing on the criterion construct, unless it could be shown that the operationalised criterion is an unbiased, reliable and valid measure of the criterion construct.

The dependency of the received incentives on irrelevant, seemingly unmistakable situational factors is a further contentious issue. A key assumption in selection validation research is that the criterion, against which the selection procedure is being evaluated, is an unbiased (i.e. uncontaminated by systematic measurement error) measure of the criterion construct. Individuals differing in terms of race, gender or geographic location, but who have the same standing on the criterion construct, should have the same chance of obtaining a specific criterion rating.

This is, however, apparently not the case. In terms of statistical analyses, the three sub-samples of CSR, PA/Specialist and Coach have been distinguished. However, the mere fact that Call Centre staff in the same group (PA1 and PA2) receive different incentives makes them non-comparable in terms of their performance on the same criterion. The fairness of the current incentive scheme is thus questionable. More importantly, however, from the perspective of the validation study, this phenomenon creates systematic variance in the criterion measure that is not explainable in terms of variance in the predictors, thus reducing the apparent validity of the predictors.

Concerning the measurement of employee performance via the performance appraisal system it must be mentioned in The Company's defense that changes are brought about consistently in an attempt to improve upon and refine the method of performance measurement. The structure of the performance appraisal system and the frequency with which the appraisals have been administered/managed at the time of the validation study have, therefore, not been known.

5.5 VALIDATION DESIGN AND SAMPLING

The term "applicant population" has not in any way been formally defined by The Company. Neither has the selection design been formally considered during the selection of the validation sample. Ironically, however, the emphasis has fallen on obtaining a representative sample of the Call Centre population, that is all those individuals who have been operational in the Call Centre for a period of at least six months.

The validation design represents the Achilles' heel of a validation study. In this case, The Company is left especially vulnerable to attack in cases of litigation due to the implied choice of validation design 5 in the Sussmann and Robertson (1986) taxonomy. The selection design seems best described as a two-phase multiple hurdle design utilising multiple selection strategies in each phase.

The intention, furthermore, seems to be to select from a totally unscreened applicant population during the first phase of selection, and to select during the second phase from the more homogenous subset of those applicants who survived the first phase. The validation sample, however, only contains individuals who have passed both phases of selection. The validation sample thus constitutes a too homogenous group (unless both phases are totally invalid) to permit the simple transportation of validation study findings on relevance, efficiency and equity to the actual operation of the selection procedure.

The size of the validation sample has, seemingly, not been affected by statistical power considerations. The required sample size has thus not been calculated *a priori* to achieve a specific, derived level of power in subsequent statistical analyses.

Statistical power should not be a problem in either the correlation analysis or the multiple regression analysis on the combined validation sample. In the case of separate analyses for Coaches, CSRs and PAs , however, problems arise with the statistical power of the correlation analysis and the multiple regression analysis performed on the Coach subset.

Assuming an effect size of 0.20, a directional alternative hypothesis and a significance level of 0.05 and given a sample size of approximately 40, the power of the test of H_0: $\rho = 0$ will only be 0.35 (Cohen, 1977). Assuming a more liberal effect size, increases in the power level to 0.60 with only a 0.35 chance of rejecting H_0: $\rho = 0$ when in fact H_0 is false, means that the *a priori* chances of finding empirical support for the procedure used for the selection of Coaches thus seem to be rather slim.

In the case of multiple regression analysis, assuming a weighted linear composite of five predictors explaining 0.25 of the variance in the criterion, a significance level of 0.05 and given a sample size of approximately 40, the *a priori* probability of rejecting H_0: $\rho = 0$ is only 0.74 (Cohen, 1977).

5.6 DATA CAPTURING

For the purpose of a subsequent validation study, data from both geographically differentiated Call Centres was obtained. The data was obtained separately, but was intended for the same purpose. However, there is insufficient information to rate the specifics of the activities regarding the data-capturing process. It is not known how the data has been captured and to what extent standardised procedures were adhered to.

What is known, however, is that complete sets of criterion and predictor data had not been obtained for all cases initially. The reason for the periodic absence in the collection of individual cases is unknown. The danger with missing data is that this can significantly influence the results obtained from statistical analyses. Depending on the nature of the missing data problem (i.e. whether the data is missing at random or whether it is systematically related to criterion and/or predictor variables), the data can be misinterpreted, and can consequently result in a misleading evaluation of the merits of a selection procedure. In addition, missing data, if left unattended, always lower the statistical power of the statistical analyses that need to be performed.

5.6 DATA SCREENING

The critical behaviours that must be executed when validating a selection procedure as mentioned in the checklist under "data screening" in Chapter VI have not been adhered to.

5.7 DATA ANALYSIS

No statistical analyses have been performed by The Company. The Company has, however, outsourced the requisite statistical analyses to the second external consultant. The analyses performed by the second external consultant, however, are not covered by this psychometric audit. From this perspective, the psychometric audit must therefore conclude that The Company, to a significant extent, lacks the evidence required to establish the efficiency and equity of the Call Centre selection procedures should they be challenged in terms of relevant equal employment opportunity legislation. Although The Company could possibly argue in defense of its Call Centre selection procedures that it does have a theoretical rationale for its choice of predictors, The Company would be unable to demonstrate the following empirically:

- The relevance or job-relatedness of the predictor information used for selection decision-making;

- ❖ The fairness with which information is combined and used in selection decision-making; and
- ❖ The utility or business necessity of the fair utilisation of relevant predictor information for selection decision-making.

In addition, The Company's failure to perform the requisite statistical analyses necessarily means that no actuarially derived decision-rule exists to dictate, on the basis of the actual (not clinically presumed) relationships that exist between the composite criterion and the individual predictors, the manner in which various pieces of predictor information should be combined for selection decision-making. Selection can only be effective if the information used for selection decision-making is systematically related to the ultimate criterion and, as important but often forgotten, if the manner in which the relevant information is combined is in agreement with the nature of the actual predictor-criterion relationships that exist in Nature.

The psychometric audit will subsequently try to remedy some of these procedural shortcomings.

CHAPTER VI

CHECKLIST FOR A PSYCHOMETRIC AUDIT OF AN ACTUARIALLY DEVELOPED PERSONNEL SELECTION PROCEDURE

6.1 INTRODUCTION

The psychometric audit aims at establishing the scientific rationality of the methodology through which the selection procedure was developed and justified. The audit essentially compares the way in which the selection procedure has actually been developed and justified with the ideal procedure derived from the Guidelines (Society of Industrial Psychology, 1998) and existing psychometric literature.

The purpose of periodic psychometric audits is to point out the degree of adherence of the selection procedure to current legislation and the Guidelines (Society of Industrial Psychology, 1998), and therefore to identify substantial and procedural shortcomings in the design and justification of the selection procedure.

The completed checklist below represents an evaluation of the current Call Centre selection procedure in terms of the critical behaviours that have to be executed when developing and justifying a seletion procedure. Furthermore, the three marked categories in the checklist below (yes; no; insufficient information to rate) are indicative of the degree to which the evaluated selection procedure can muster valid and credible evidence as proof of its relevance, utility and fairness. As will become evident, however, substantial and procedural shortcomings in the existing design and justification of the selection procedure have been identified.

6.2 CHECKLIST DEVELOPED FOR A PSYCHOMETRIC AUDIT

Table 6.1 Checklist developed for a psychometric audit

ACTIVITY	YES	NO	INSUFFICIENT INFORMATION TO RATE
I. JOB ANALYSIS			
1.1 A systematic and thorough job analysis has been performed.	✓		
1.2 The nature of the job analysis has been well documented.			?
1.3 A representative sample of SME has been used for the job analysis.			?
1.4 A reputable and reliable job analysis technique has been used to obtain information concerning the content of the job in question.	✓		
1.5 The job analysis technique has been administered on a valid, representative sample of job incumbents for the specific job.	✓		
1.6 The job analysis clearly and comprehensively specifies the context in which the job is performed.	✓		
1.7 A formal job description has been compiled and documented.	✓		
II. PREDICTOR DEVELOPMENT			
2.1 An empirical, logical and theoretical foundation exists for each of the chosen predictor variables (e.g. relevant previous research).			?
2.2 All the predictor constructs contained in the performance hypothesis have been constitutively defined.			?
2.3 All predictor constructs ξ_I contained in the performance hypothesis have been operationalised in terms of predictor measures.			?
2.4 All predictor measures have been empirically item analysed.			?

2.5 All predictor measures have been empirically examined for differential item functioning or item bias.			?
2.6 All predictor measures have been well standardised.		×	
2.7 Empirical evidence has been obtained to establish the (construct) validity of the predictors utilised.		×	
2.8 Empirical evidence on the (construct) validity of all predictor measures has been well documented.		×	
2.9 Empirical evidence on the reliability of all predictor measures has been obtained and well documented.	✓		
2.10 All the predictors are administered and scores according to the test manual's directives on standardisation.			?
III. CRITERION DEVELOPMENT			
3.1 The criterion construct η to be predicted has been identified.	✓		
3.2 The final/ultimate criterion η has been explicitly behaviourally conceptualised through a formal constitutive definition.			?
3.3 The constitutive definition of η was derived from a job description.			?
3.4 The constitutive definition of η explicates the internal structure of the criterion construct in terms of performance dimensions η_I and their inter-relationships.			?
3.5 The constitutive definition of η_I explicates the relationships between η_I and the outcomes implied by the objectives of the position.			?
3.6 The constitutive definition of η_I contains sufficient information to construct a comprehensive LISREL model (including both measurement and structural models).			?
3.7 Operational criterion measures have been developed to assess η_i.	✓		
3.8 The operational criterion measure has been qualitatively evaluated in terms of criterion deficiency.		×	

3.9 The operational criterion measure has been qualitatively evaluated in terms of criterion contamination.		×	
3.10 The operational criterion measure has been qualitatively evaluated in terms of criterion relevance (content validity).		×	
3.11 All operational criterion constructs have been empirically item analysed.		×	
3.12 The operational criterion measure has been empirically examined for differential item functioning or item bias.		×	
3.13 The operational criterion measure has been well standardised.		×	
3.14 Empirical estimations of the reliability of the operational criterion measure have been obtained.		×	
3.15 The factorial validity of the operational criterion measures has been empirically estimated through confirmatory factor analysis (LISREL/SEM).		×	
3.16 The choice as to whether operational criterion measures are to be combined into a composite or whether multiple criteria are to be used has been considered and justified.		×	
3.17 Weights used in the composite criterion or in the multiple criterion has been established empirically.		×	
IV. VALIDATION DESIGN AND SAMPLING			
4.1 The applicant population has been defined.		×	
4.2 The validation design has clearly been defined.		×	
4.3 The selection design has clearly been defined.		×	
4.4 The validation design has been evaluated in terms of internal validity.		×	
4.5 The validation design has been evaluated in terms of external validity.		×	
4.6 The validation design corresponds to the selection design and thus has high external validity.		×	
4.7 The validation group constitutes a representative sample of the applicant population.		×	

4.8 The required sample size has been calculated a priori to achieve a specific desired level of power in correlation and multiple regression analyses.		X	
4.9 The statistical power of subsequent correlation and regression analyses has been examined given the size of the actual validation sample.		X	
V. DATA CAPTURING			
5.1 The administration and scoring of predictors has been monitored to be in accordance with test manuals' directives.			?
5.2 The gathering of criterion information has been monitored to be in accordance with test manuals' directives.			?
5.3 Complete sets of criterion and predictor data have been obtained for all cases initially selected into the validation sample.		X	
5.4 Predictor data has been collected independently of criterion data.			?
VI. DATA SCREENING			
6.1 The accuracy of the data entered into the computer has been checked.			?
6.2 Assumptions of normality, linearity and homoscedasticity have been checked.		X	
6.3 The problem of missing values, if present, has been considered.		X	
6.4 Missing values have been replaced if necessary.		X	
6.5 The presence of outliers has been checked.		X	
VII. DATA ANALYSIS: CORRELATION ANALYSIS			
7.1 All possible predictor-criterion, inter-predictor and inter-criterion correlations observable from the correlation matrix have been calculated.		X	
7.2 The correlations between clinically derived inferences and criterion measures have been calculated (i.e. all clinical opinions are formally acknowledged as predictors).		X	

7.3 The statistical significance of all the correlations contained in the correlation matrix has been determined.		×	
7.4 The validity coefficients have been appropriately corrected for the attenuating effect of criterion unreliability, if necessary.		×	
7.5 The validity coefficients have been appropriately corrected for restriction of range, if necessary.		×	
7.6 The validity coefficients have been corrected for systematic criterion contamination, if necessary.		×	
7.7 The corrected and/or uncorrected validity coefficients have been correctly interpreted in terms of significance.		×	
7.8 The corrected and/or uncorrected validity coefficients have been correctly interpreted in terms of the coefficient of determination and the coefficient of non-determination.		×	
7.9 The corrected and/or uncorrected validity coefficients have been correctly interpreted in terms of the coefficient of non-determination.		×	
VIII. DATA ANALYSIS: MULTIPLE REGRESSION ANALYSIS			
8.1 Stepwise multiple regression analysis has been used as an exploratory technique, in addition to the correlation matrix, to assist in the identification of predictors for their inclusion in the selection battery.		×	
8.2 Standard multiple regression analysis has been performed to determine the weighted linear combination of predictors.		×	
8.3 Residual plots have been generated to examine the normality, linearity and homoscedasticity assumptions underlying multiple regression.		×	
8.4 The presence of univariate and multivariate outliers has been examined.		×	
8.5 Squared partial and semi-partial correlations have been calculated to assess the relative importance of predictors in the regression model.		×	

8.6 Standardised regression coefficients have been calculated to assess the relative importance of predictors in the regression model.		×	
8.7 The validity of the weighted linear combination of predictors has been corrected for shrinkage with the use of shrinkage formulas.		×	
8.8 The regression of the composite criterion on the weighted linear combination of predictors has been cross-validated on an independent cross validation sample.		×	
8.9 A criterion-referenced norm table, reflecting the probability of failure or success conditional on expected criterion performance, has been calculated.		×	
8.10 An explicit decision-rule has been formulated in terms of expected criterion performance and/or in terms of probability of failure conditional on a weighted linear (or non-linear) combination of predictors.		×	
8.11 If multiple predictors have been combined non-linearly, this decision has been considered carefully.		×	
8.12 All sources of information used in the selection decision-making have been included in the formal decision-rule.		×	
IX. DATA ANALYSIS: FAIRNESS ANALYSIS			
9.1 The decision-rule's selection fairness has been examined empirically in terms of the Cleary interpretation of fairness with the use of multiple regression.		×	
9.2 Differential and single group validity has been examined.		×	
9.2 The decision-rule's selection fairness, with the use of multiple regression, has empirically been examined in terms of the Einhorn-Bass interpretation of fairness.		×	
9.4 The decision-rule's selection fairness has been empirically examined in terms of the Thorndike interpretation of fairness.		×	
9.5 The variables of race and gender formed the basis for the fairness analysis.		×	

9.6 A criterion-referenced norm table reflecting the probability of failure (or success) conditioned on expected criterion performance and group membership has been calculated, if necessary.		×	
9.7 The explicit decision-rule, formulated in terms of expected criterion performance and/or probability of failure conditional on a weighted linear (or non-linear) combination of predictors, has been revised so as to rectify any existing selection fairness problems.		×	
X. DATA ANALYSIS: UTILITY ANALYSIS			
10.1 Selection utility has empirically been examined in terms of the Taylor-Russell interpretation of utility.		×	
10.2 Selection utility has empirically been examined in terms of the Naylor-Shine interpretation of utility.		×	
10.3 An estimate of the standard deviation of the composite criterion distribution scaled in a monetary metric has empirically been derived.		×	
10.4 Selection utility has empirically been examined in terms of the basic Brodgen-Cronbach-Gleser interpretation of utility.		×	
10.5 Selection utility has empirically been examined in terms of the elaborated Boudreau interpretation of utility.		×	
XI. MISCELLANEOUS			
11.1 A formal selection policy has been compiled and documented.			?

CHAPTER VII

RESEARCH FINDINGS

7.1 INTRODUCTION

The research findings reported below represent the results of a continuation of the description of the current selection procedure as described in Chapter IV.

Statistical analyses are necessary in any validation study in determining the scientific credibility and validity of an existing selection procedure in terms of which the selection of individuals in a specified position can be justified, and thereby defended, in cases of litigation. It is for this reason that the Author has performed the various statistical analyses that have not been performed by The Company, but that are required to demonstrate the relevance, efficiency and equity of the selection decision-making. The obtained research findings are thus related to the different aspects involved in statistical validation analyses as set out in the checklist in Chapter VI.

7.2 ITEM AND RELIABILITY ANALYSIS

Each of the performance questionnaire sub-scales were item analysed through the SPSS reliability procedure (SPSS, 1990) to identify and eliminate items not contributing to an internally consistent description of the performance area/competency in question. No items needed to be deleted from any of the sub-scales on any one of the three performance questionnaires.

The reliability of the questionnaires has been quantitatively evaluated in terms of each of the different sub-scales on each of the questionnaires developed for the CSR, PA and Coach. The Alpha coefficients (α) for each sub-scale on each of the three questionnaires are illustrated in Table 7.1 below.

The factorial validity of the three performance questionnaires was not examined. The ideal would be to perform a confirmatory factor analysis on each of the three questionnaires, preferably utilising structural equation modeling.

Table 7.1 Alpha coefficients for questionnaire sub-scales

Questionnaire sub-scale	α-coefficient: Coach	α-coefficient: CSR	α-coefficient: PA
Interpersonal sensitivity	0.9508	0.9470	Not applicable
Teamwork	0.9229	Not applicable	Not applicable
Achievement Orientation	0.9692	Not applicable	Not applicable
Decisiveness and Execution	0.9323	Not applicable	Not applicable
Analysis	0.97390	Not applicable	Not applicable
Decision-making	0.9574	Not applicable	Not applicable
Goal setting and management control	0.9160	Not applicable	Not applicable
Development and empowerment of others	0.9609	Not applicable	Not applicable
Client service orientation	Not applicable	0.9638	0.9385
Communication	Not applicable	0.9647	0.9415
Performance orientation	Not applicable	0.9572	0.9456
Perseverance	Not applicable	0.9390	0.9422
Self-control	Not applicable	0.9477	Not applicable
Eagerness to learn	Not applicable	0.9501	0.8967
Identifying and solving problems	Not applicable	0.9501	0.9683
Total reliability	**0.9916**	**0.9880**	**0.9845**

7.3 CORRELATION ANALYSIS

An inter-predictor, inter-criterion and predictor-criterion correlation matrix was calculated for each of the three Call Centre positions separately. The calculation of three separate correlation matrices was necessitated by the fact that the performance questionnaire differed across the three positions.

7.3.1 Correlation Analysis: Coach

The inter-predictor, inter-criterion and predictor-criterion correlation matrix for Coaches is shown in Table A.1 in Appendix A. Table 7.2 provides an explanation of the variable names used in the correlation analysis.

Table 7.2 Variable names used in the Coach correlation analysis in alphabetical order

Criterion variables	Predictor variables
ACHIEVE = Achievement Orientation	CSANAL = Case Study Analysis
ANALYSIS = Analysis	CSDEC = Case Study Decision-making
DECISION = Decision-making	NUMANAL = Numerical Analysis
DECISIVE = Decisiveness and Execution	OPQACHOR = OPQ Achievement Orientation
DEVEMP = Development and Empowerment of Others	OPQANAL = OPQ Analysis
GOALSET = Goal Setting and Management Controls	OPQCSO = OPQ Client Service Orientation
INTSENS = Interpersonal Sensitivity	OPQDEC = OPQ Decision-making
PERFMEAS = Performance Measure	OPQDECEX = OPQ Decisiveness and Execution
TEAMWORK = Teamwork	OPQDEMP = OPQ Development and Empowerment of Others
TOTCOACH = Total Coach	OPQISEN = OPQ Interpersonal Sensitivity
-	OPQOSMC = OPQ Objective Setting and Management Control
-	OPQTEAM = OPQ Teamwork
-	RPACHOR = Role Play Achievement Orientation
-	RPCSO = Role Play Client Service Orientation
-	RPDEMP = Role Play Development and Empowerment of Others
-	RPISEN = Role Play Interpersonal Sensitivity
-	RPOSMC = Role Play Objective Setting and Management Control
-	TOTACHOR = Total Achievement Orientation
-	TOTANAL = Total Analysis
-	TOTCSO = Total Client Service Orientation
-	TOTDEC = Total Decision-making
-	TOTDECEX = Total Decisiveness and Execution
-	TOTDEMP = Total Development and Empowerment of Others
-	TOTISEN = Total Interpersonal Sensitivity
-	TOTOSMC = Total Objective Setting and

	Management Control
-	TOTTEAM = Total Teamwork
-	VERBANAL = Verbal Analysis

Table A.1 firstly indicates high to extremely high and significant ($p < 0.05$) correlations between the eight sub-scales comprising the behavioural performance questionnaire for Coaches. This should be regarded as problematic, since it would suggest the presence of a single underlying performance factor that is in all probability not in accordance with the implicit constitutive definition of the criterion construct for Coaches.

An even more disturbing finding is that the incentive measure of performance (PERFMEAS) correlates insignificantly ($p > 0.05$) with each of the eight behavioural performance measure sub-scales and with the composite behavioural performance measure (TOTCOACH). This finding seriously undermines the credibility of the incentive measure of Coach performance. The credibility of the latter performance measure is further weakened by the finding that all of the predictor-PERFMEAS correlations are insignificant ($p > 0.05$).

Table A.1 presents a rather bleak picture regarding the predictive validity of the predictors utilised in the selection of Call Centre Coaches. The majority of predictors show a weak and insignificant ($p > 0.05$) correlation with the composite behavioural performance measure (TOTCOACH). There are two exceptions: TOTACHOR correlates 0.36712 ($p < 0.05$) with TOTCOACH and RPACHOR correlates 0.33656 ($p < 0.05$) with TOTCOACH. Support thus seems to exist for the hypothesis that Achievement Orientation affects the performance of Call Centre Coaches. The fact that the OPQ measure of Achievement Orientation (OPQACHOR) correlates weakly and insignificantly ($r = 0.07311$; $p > 0.05$) with TOTCOACH, however, again tends to point to the opposite conclusion.

When looking at the correlations between the predictors and the individual components of the composite performance measure, a somewhat more positive picture emerges. The role play measure of Decisiveness and Execution (RPDECEX) shows moderate and significant ($p < 0.05$) correlations with DECISIVE, ANALYSIS, DECISION, GOALSET and DEVEMP. This trend seems to fade, however, when the separate performance measures are combined in a composite criterion measure. The role play measure of Objective Setting and Management Control (RPOSMC) correlates moderately and significantly ($p < 0.05$) with GOALSET and DEVEMP.

The OPQ measures show disappointing results. Only the OPQ measure of Objective Setting and Management Control (OPQOSMC) correlates moderately negatively and significantly ($p < 0.05$) with DECISION, but not significantly ($p > 0.05$) with GOALSET and DEVEMP as does the role play measure of the same construct.

Verbal Analysis (VERBANAL) correlates negatively and significantly ($p < 0.05$) with ACHIEVE, while VERBANAL and NUMANAL both correlate negatively and significantly ($p < 0.05$) with DECISION.

The combined measure of Decisiveness and Execution (TOTDECEX) correlates significantly ($p < 0.05$) with five of the individual performance measures, but possibly partially due to the high inter-correlations amongst performance measures, this trend again fades out when the performance measures are combined in a composite performance measure. Finally, the combined measure of Teamwork (TOTTEAM) shows a moderate negative significant ($p < 0.05$) correlation with GOALSET, and TOTOSMC shows a moderate significant positive correlation with DEVEMP.

Given the nature of the validation design, the validity coefficients reported should be regarded as negatively biased due to restriction of range. The calculated validity coefficients should thus be corrected for Case A restriction of range. However, since no estimates of the unrestricted predictor variances were available (probably due to insufficient attention to the quality of the validation design prior to the gathering of data), however, the appropriate corrections to the validity coefficients could not be made. It should be remembered that, although these corrections would have increased the magnitude of the validity coefficients, this would not necessarily affect the significance of the correlations since the standard error of the correlation is also affected.

7.3.2 Correlation Analysis: CSR

The inter-predictor, inter-criterion and predictor-criterion correlation matrix for the CSR group is shown in Table A.2 in Appendix A. Table 7.3 provides an explanation of the variable names used in the correlation analysis.

Table 7.3 Variable names used in the CSR correlation analysis in alphabetical order

Criterion variables	Predictor variables
INSEN = Interpersonal Sensitivity	CCSQCOOP = CCSQ Co-operation
CLIENTSO = Client Service Orientation	CCSQCOMM = CCSQ Communication
COMMUNIC = Communication	CCSQCSO = CCSQ Client Service Orientation
PERSEVER = Perseverance	CCSQEL = CCSQ Eagerness to Learn
SELFCONT = Self-control	CCSQHI = CCSQ Handling Information
EAGERNES = Eagerness to Learn	CCSQISEN = CCSQ Interpersonal Sensitivity
IDENTSOL = Identifying and Solving Problems	CCSQISP = CCSQ Identifying and Solving Problems
PERFMEAS = Performance Measure	CCSQPERF = CCSQ Performance Orientation
TOTCSR = Total CSR	CCSQPERS = CCSQ Perseverance
-	CCSQSELF = CCSQ Self-control
-	CHECKHI = Clerical Checking Handling Information
-	CLASSHI = Classification Handling Information
-	CSHI = Case Study Handling Information
-	CSISP = Case Study Identifying and Solving Problems
-	CSPERF = Case Study Performance Orientation
-	CSPERS = Case Study Perseverance
	RPISEN = Role Play Interpersonal Sensitivity
-	RPISP = Role Play Identifying and Solving Problems
-	RPPERF = Role Play Performance Orientation
-	RPSELF = Role Play Self-confidence
-	TOTCOMM = Total Communication
-	TOTCOOP = Total Co-operation
-	TOTCSO = Total Client Service Orientation
-	TOTEL = Total Eagerness to Learn
-	TOTHI = Total Handling Information
-	TOTISEN = Total Interpersonal Sensitivity
-	TOTISP = Total Identifying and Solving Problems
-	TOTPERF = Total Performance Orientation
-	TOTPERS = Total Perseverance
-	TOTSELF = Total Self-control
-	VERBHI = Verbal Handling Information
-	VERBISP = Verbal Identifying and Solving Problems

Table A.2 in Appendix A firstly indicates moderate to high and significant ($p < 0.05$) correlations between the eight sub-scales comprising the behavioural performance questionnaire for CSRs. The significant correlations should be regarded as problematic, since it would suggest the presence of a single underlying performance factor that is probably not in accordance with the implicit constitutive definition of the criterion construct for CSRs.

A positive finding is that the incentive measure of performance (PERFMEAS) correlates moderately and significantly ($p < 0.05$) with each of the eight behavioural performance measure sub-scales and with the composite behavioural performance measure (TOTCSR). This finding supports the credibility of the incentive measure of CSR performance, although the correlation with TOTCSR is only moderate ($r = 0.36703$). Despite the apparent credibility of the PERFMEAS performance measure, however, the majority of the predictor-PERFMEAS correlations are insignificant ($p > 0.05$). This finding undermines the credibility of the incentive measure of CSR performance. There are, however, a few exceptions.

The case study performance measures of Handling Information (CSHI) and Perseverance (CSPERS), the combined measures of Handling Information (TOTHI) and Perseverance (TOTPERS), as well as CLASSHI and CHECKHI correlate low and significantly ($p < 0.05$) with PERFMEAS. VERBHI correlates negatively, low and significantly ($p < 0.05$) with PERSMEAS.

Table A.2 again presents a rather bleak picture regarding the predictive validity of the predictors utilised in the selection of Call Centre CSRs. The majority of predictors show very weak and insignificant ($p > 0.05$) correlations with the composite behavioural performance measure (TOTCSR). Only three exceptions occur: CSHI correlates 0.19391 ($p < 0.05$); CLASSHI correlates 0.21637 ($p < 0.05$); and TOTHI correlates 0.23874 ($p < 0.05$) with TOTCSR. There thus seems to be support for the hypothesis that Handling Information affects the performance of Call Centre CSRs. The fact that the CCSQ measure of Handling Information (CCSQHI) and the PTB measure of Handling Information (VERBHI) correlate very weakly and insignificantly ($p > 0.05$) with TOTCSR ($r = 0.04060$ and $r = -0.14663$ respectively), however, tends to point to the opposite conclusion.

When looking at the correlations between the predictors and the individual components comprising the behavioural performance questionnaire for CSRs, a somewhat more positive picture emerges. TOTEL and TOTHI correlate low and significantly ($p < 0.05$) with INSEN. VERBHI, CHECKHI, CLASSHI and TOTHI correlate low and significantly ($p < 0.05$) with CLIENTSO. CHECKHI, CLASSHI and TOTHI correlate low and significantly ($p < 0.05$) with the behavioural subscale measure of Communication.

The case study measures of Identifying and Solving Problems (CSISP); Handling Information (CSHI); Performance Orientation (CSPERF) and Perseverance (CSPERS) all correlate low and significantly ($p < 0.05$) with PERFOR. CSHI, CSPERF and TOTPERS are the predictors that correlate low and significantly ($p < 0.05$) with PERSEVER.

CLASSHI and TOTHI are the only two predictor measures that show significant correlations with IDENTSOL. CSHI is the only predictor that correlates low and significantly ($p < 0.05$) with the behavioural sub-scale measure of Eagerness to Learn (EAGERNES).

These reported significant predictor-criterion dimension correlations would have been far more valuable if they could have been interpreted against the backdrop of a comprehensive LISREL model depicting the expected relationships between the predictor and criterion latent variables comprising the performance hypothesis (i.e. a structural model) as well as the various operational measures of the latent variables (i.e. the exogenous and endogenous measurement models). Only when the interpretation of the correlation matrix takes an explicit, comprehensive LISREL model as its point of departure does selection validation really become hypothesis testing in the sense that Landy (1986) and Ellis and Blustein (1991) mean it.

If these reported correlations would turn out to be in agreement with such a model, the probability of a multiple cut-off selection strategy should be investigated and compared to a multiple regression strategy predicting a composite criterion. In terms of the multiple cut-off strategy, linear components of predictors would be developed to predict performance on each of the performance dimensions comprising the composite criterion.

Once again, it is important to realise that the calculated validity coefficients should be corrected for Case A restriction of range. However, since no estimates of the unrestricted predictor variances were available (probably due to insufficient attention to the quality of the validation design prior to the gathering of data), however, the appropriate corrections to the validity coefficients could not be made. It should be remembered that, although these corrections would have increased the magnitude of the validity coefficients, this would not necessarily affect the significance of the correlations since the standard error of the correlation is also affected.

7.3.3 Correlation Analysis: PA

The inter-predictor, inter-criterion and predictor-criterion correlation matrix for PAs is shown in Table A.3 in Appendix A. Table 7.4 provides an explanation of the variable names used in the correlation analysis.

Table 7.4 Variable names used in the PA correlation analysis in alphabetical order

Criterion variables	Predictor variables
CLIENTSO = Client Service Orientation	CCSQCOMM = CCSQ Communication
COMMUN = Communication	CCSQCOOP = CCSQ Co-operation
EAGERNES = Eagerness to Learn	CCSQCSO = CCSQ Client Service Orientation
IDSOLPRO = Identifying and Solving Problems	CCSQEL = CCSQ Eagerness to Learn
PERFMEAS = Performance Measure	CCSQHI = CCSQ Handling Information
TOTPA = Total PA	CCSQISP = CCSQ Identifying and Solving Problems
-	CCSQPERF = CCSQ Performance Orientation
-	CCSQPERS = CCSQ Perseverance
-	CCSQSELF = CCSQ Self-control
-	CHECKHI = Clerical Checking Handling Information
-	CLASSHI = Classification Handling Information
-	CSCSO = Case Study Client Service Orientation
-	CSISP = Case Study Identifying and Solving Problems
-	CSPERF = Case Study Performance Orientation
-	CSPERS = Case Study Perseverance
-	NUMISP = Numerical Identifying and Solving Problems
-	TOTCOMM = Total Communication
-	TOTCOOP = Total Co-operation
-	TOTCSO = Total Client Service Orientation
-	TOTEL = Total Eagerness to Learn
-	TOTHI = Total Handling Information
-	TOTISEN = Total Interpersonal Sensitivity
-	TOTISP = Total Identifying and Solving Problems
-	TOTPERF = Total Performance Orientation
-	TOTPERRS = Total Perseverance
-	TOTSELF = Total Self-control

Table A.3 firstly indicates high to extremely high and significant ($p < 0.05$) correlations between the eight sub-scales comprising the behavioural performance questionnaire for PAs. This should be regarded as problematic, since it would suggest the presence of a single underlying performance factor that is probably not in accordance with the implicit constitutive definition of the criterion construct for PAs.

A somewhat more positive finding is that the incentive measure of performance (PERFMEAS) correlates significantly ($p < 0.05$) with about half of the eight behavioural performance measure sub-scales. The magnitude of the significant correlations between PERFMEAS and the individual performance dimensions is, however, moderate to low. This finding, to a limited extent, strengthens the credibility of the incentive measure of PA performance. However, the credibility of the incentive performance measure (PERFMEAS) is weakened by the finding that only six predictor-PERFMEAS correlation are significant ($p < 0.05$), that is CSPERF, CSPERS, CCSQHI, CCSQPERF, TOTPERF and TOTPERS correlate significantly ($p < 0.05$) with PERFMEAS.

Table A.3 in Appendix A presents a slightly more positive picture regarding the predictive validity of the predictors utilised in the selection of Call Centre PAs. Although the majority of predictors show a weak and insignificant ($p > 0.05$) correlation with the composite behavioural performance measure (TOTPA), eight exceptions occur.

CCSQHI correlates 0.20689 ($p < 0.05$), CCSQCOOP correlates -0.28358 ($p < 0.05$) and CCSQPERF correlates 0.22585 ($p < 0.05$) with TOTPA. Furtermore, the PTB measures of CHECKHI and CLASSHI, and the CCAS measure of NUMISP correlate significantly ($p < 0.05$) with the composite behavioural performance measure (TOTPA). TOTCOOP ($r = -0.31290$) and TOTPERS ($r = 0.18642$) also correlate significantly ($p < 0.05$) with TOTPA.

When looking at the correlations between the predictors and the individual components comprising the behavioural performance questionnaire for CSRs, a somewhat more positive picture once again emerges. The CCSQ measure of Handling Information (CCSQHI) shows low and significant ($p < 0.05$) correlations with CLIENTSO, PERFORIE, PERSEVER and EAGERNES. A positive sign is also that CCSQHI correlates significantly ($p < 0.05$) with the incentive measure of performance and with the composite behavioural performance measure.

The correlation of the CCSQ performance measure of Co-operation (CCSQCOOP) looks even more positive. CCSQCOOP correlates negatively and significantly ($p < 0.05$) with six of the sub-scales comprising the behavioural performance questionnaires for PAs, namely with CLIENTSO, COMMUN, PERFORIE, PERSEVER, EAGERNES and IDSOLPRO. A rather puzzling finding, however, is that although CCSQCOOP correlates significantly ($p < 0.05$) with the composite behavioural performance measure of TOTPA, it correlates highly insignificantly ($p > 0.05$) with the incentive PA performance measure.

The same scenario is relevant to TOTCOOP. TOTCOOP shows negative and significant ($p < 0.05$) correlations with the same predictors as the CCSQ measure of Co-operation. Again, although TOTCOOP correlates significantly ($p < 0.05$) with TOTPA, it correlates insignificantly ($p > 0.05$) with the incentive measure of performance (PERFMEAS) for PAs.

CCSQPERF shows significant ($p < 0.05$) correlations with CLIENTSO ($r = 0.24557$) and with PERSEVER ($r = 0.31119$). CHECKHI correlates significantly ($p < 0.05$) with all of the eight behavioural performance measure sub-scales, except for COMMUN ($p > 0.05$) and PERFMEAS ($p > 0.05$). CLASSHI also correlates significantly ($p < 0.05$) with all of the eight behavioural performance measure sub-scales, except for its insignificant ($p > 0.05$) correlations with IDSOLPRO and PERFMEAS.

Although NUMISP correlates significantly ($p < 0.05$) only with CLIENTSO ($r = 0.24651$) and EAGERNES ($r = 0.27452$), it interestingly still correlates significantly ($p < 0.05$) with TOTPA. Regarding the combined predictor measures of TOTHI and TOTPERF, it is interesting to note that TOTHI correlates significantly ($p < 0.05$) with three of the eight sub-scales (CLIENTSO, PERFORIE and PERSEVER), but not with either PERFMEAS or TOTPA. However, TOTPERF, which correlates significantly ($p < 0.05$) only with one of the eight sub-scales, correlates significantly ($p < 0.05$) with PERFMEAS. TOTPERS correlates significantly ($p < 0.05$) with CLIENTSO, PERSEVER and IDSOLPRO.

It is important to realise that the calculated validity coefficients should again be corrected for Case A restriction of range. Since no estimates of the unrestricted predictor variances were available (probably due to insufficient attention to the quality of the validation design prior to the gathering of data), the appropriate corrections to the validity coefficients could not be made. It should be remembered that although these corrections would have increased the magnitude of the validity coefficients, they would not necessarily affect the significance of the correlations since the standard error of the correlation is also affected.

7.4. Correlation Analysis: Concluding Remarks

From the correlation analyses it is evident that in the case of all three positions, the correlations between some latent variables that were measured by different assessment instruments did not correlate statistically significantly. The dearth of statistically significant correlations among supposedly similar predictor variables thus results in the undermining of the convergent validity of the relevant measuring instruments. The same comments also apply to the criterion measures.

Furthermore, the few statistically significant ($p < 0.05$) and low correlations between the predictor and criterion variables are indicative of a relatively low predictive validity. This seems to suggest the need for additions and alterations to the performance hypothesis. The current performance hypothesis should thus be made explicit, preferably in the form of a structural nomological model. The current performance hypothesis should be examined critically to identify redundant exogenous constructs and paths that can be pruned away, and to identify new exogenous constructs that need to be added to the model. This line of reasoning, however, rests on the assumption that the psychometric quality of the predictor and criterion measures in this data set were above suspicion.

7.5 MULTIPLE REGRESSION ANALYSIS

7.5.1 Multiple Regression Analysis: Coach

The goal of the multiple stepwise regression procedure performed is the identification of the smallest sub-set of predictors able to explain the greatest proportion criterion variance. Variables were identified for inclusion in the stepwise regression analysis from the correlation matrix shown in Table A.1 in Appendix A. The list of predictor variables included in the stepwise regression analysis are shown in Table 7.5.

Table 7.5 Variables included in the Coach stepwise regression analysis

1. TOTACHOR	9. TOTDEMP
2. RPACHOR	10. TOTOSMC
3. RPCSO	11. OPQDECEX
4. RPDECEX	12. OPQACHOR
5. RPDEMP	13. OPQDEMP
6. RPOSMC	14. OPQDEC
7. TOTCSO	15. VERBANAL
8. TOTDECEX	

The first two variables were included due to their significant correlation with the composite criterion. Due to the high positive and significant ($p < 0.05$) correlation between them, the probability of inclusion of both variables in a linear composite of predictors is practically zero. The remainder of the predictor variables were allowed to compete for inclusion in the predictor battery due to their significant correlation with the first two predictors combined with their insignificant correlations with the composite criterion. The significance levels for entry into the model (SLE) and for staying in the model (SLS) were initially set at 0.10.

From the multiple stepwise regression analysis for the Coach sub-sample shown in Table B.1 in Appendix B, it is evident that only TOTACHOR has been identified, from the entire list of predictors with which Coaches were selected, as the predictor to contribute statistically significantly ($p = 0.0143$) to the overall dependent variable, TOTCOACH. No other individual predictor considered relevant to the selection of Coaches could significantly explain additional variance in the composite criterion when added to the battery. It is further disturbingly evident that only approximately 15.15% ($R^2 = 0.15145558$) of the variation in the dependent variable TOTCOACH can be explained in terms of TOTACHOR. Subsequently, the SLE and SLS values were both increased to 0.15 to examine the possibility that sub-sets of predictors might warrant inclusion in the model, but only if added as a block and not individually.

Five predictor variables were identified for inclusion. The significance level was liberally set at 0.1 to allow for greater predictor inclusion into the regression model. TOTACHOR, OPQDECEX, OPQACHOR, VERBANAL and OPQDEMP each significantly ($p < 0.1$) explains unique variance in the composite criterion not explained by the other predictors included in the battery. The reason for the inclusion of this specific subset of predictors in the battery is hard to explain. The prudent option would probably be to be highly skeptical of this finding in view of the fact that no theoretical rationale exists for the particular combination of predictors.

Standard multiple regression was subsequently performed to examine the weighted linear combination of predictors a bit more thoroughly. The output of the standard multiple regression analysis differs slightly from that of the stepwise regression analysis due to a slight difference in the number of observations included in the analysis.

From the standard multiple regression analysis performed on the sub-sample of Coaches (Table B.1, Appendix B), it is evident that 45.21% ($R^2 = 0.4521$) of the variation in the dependent criterion variable can be explained in terms of the weighted linear combination of the following variables: TOTACHOR, OPQDECEX, OPQACHOR, VERBANAL and OPQEMP. The linear combination of predictors correlates statistically significantly ($p = 0.0007$) with the composite criterion. The significance of OPQDEMP is borderline ($p = 0.0636$), while the remaining four predictors TOTACHOR ($p = 0.0036$), OPQDECEX ($p = 0.0010$), OPQACHOR ($p = 0.0115$), and VERBANAL ($p = 0.0208$) all significantly ($p < 0.05$) explain unique variance in the composite criterion.

Furthermore, it can be noted that, when examining the regression coefficient parameter estimates, OPQDECEX seems to be the most influential predictor (parameter estimate = -127.593901). However, the parameter estimate can provide a misleading indication of the relative importance of a predictor in a regression model due to the fact that the predictors are not measured in the same units, and due to the fact that the predictors statistically overlap in terms of their individual contribution to the variance in the composite dependent criterion variable. To solve the problem of measurement in unequal units, the standardised estimate (β-value) is examined, from which it is evident that OPQDECEX is in fact the most powerful predictor in terms of the average change in the criterion associated with one standard deviation change in the standardised predictor. To solve the problem of overlap, it is important to examine the Type II squared partial and semi-partial correlations.

Squared partial correlation refers to the proportion of unique criterion variance in the dependent variable explained by the unique variance in the independent variable. Thus, examining the most powerful predictor, approximately 27.50% (squared partial correlation = 0.27496080) of the variance in TOTCOACH, which is not explained by the other predictors, is explained by the unique variance in OPQDECEX.

Squared semi-partial correlation refers to the proportion of the total variance in the dependent variable explained by the unique variance in the predictor not shared by the other independent variables. Examining OPQDECEX, approximately 20.78% (squared semi-partial correlation = 0.20776807) of the unique variance in OPQDECEX (in other words the variance in OPQDECEX not explained by any of the other predictors) can be associated with the total variance in the dependent variable, TOTCOACH. Thus, 20.78% of the TOTCOACH variance can be explained in terms of the unique OPQDECEX variance.

The prominence of the OPQ predictors relevant to TOTACHOR in the predictor battery again constitutes a somewhat surprising result.

7.5.2 Multiple Regression Analysis: CSR

The goal of the multiple stepwise regression procedure performed is the identification of the smallest sub-set of predictors able to explain the greatest proportion criterion variance. Variables were identified for inclusion in the stepwise regression analysis from the correlation matrix shown in Table A.2 in Appendix A. The list of predictor variables included in the stepwise regression analysis are shown in Table 7.6.

The first three variables were included due to their significant correlation with the composite criterion. Due to the high positive and significant ($p < 0.05$) correlation between CLASSHI and TOTHI, the probability of inclusion of both variables in a linear composite of predictors is practically zero. The remainder of the predictor variables were allowed to compete for inclusion in the predictor battery due to their significant correlation with the first three predictors combined with their insignificant correlations with the composite criterion. The significance levels for entry into the model (SLE) and for staying in the model (SLS) were set at 0.15.

Table 7.6 Variables included in the CSR stepwise regression analysis

1. CSHI	8. TOTPERS
2. CLASSHI	9. VERBISP
3. TOTHI	10. CHECKHI
4. CSISP	11. NUMISP
5. CSPERF	12. TOTPERF
6. CSPERS	13. VERBHI
7. CCSQPERF	14. RPCOMM
	15. TOTCOMM

From the multiple stepwise regression analysis for the CSR sub-sample shown in Table B.2 in Appendix B it is evident that, with the significance level liberally set at 0.1, TOTHI, CSHI and VERBHI have been identified as the predictors, from the entire list of predictors with which CSRs were selected, to contribute statistically significantly ($p = 0.016$, $p = 0.0735$, $p = 0.0674$ respectively) to TOTCSR. The statistical significance ($p < 0.1$) at which CSHI and VERBHI explain unique variance in the composite criterion not explained by the other predictors included in the battery is borderline.

The inclusion of the first two variables that entered the regression model can be explained by the fact that CSHI and TOTHI correlate significantly ($p < 0.05$) with the criterion but insignificantly ($p > 0.05$) with each other. The inclusion of the last variable can be explained by the fact that VERBHI correlates low but significantly ($p < 0.05$) with TOTHI. The prudent option would probably be to be highly skeptical of this finding in view of the fact that no *a priori* theoretical rationale exists for the particular combination of predictors. No other individual predictor considered relevant to the selection of CSRs could significantly explain additional variance in the composite criterion when added to the battery. It is further disturbingly evident that only approximately 11% ($R^2 = 0.10973582$) of the variation in the dependent variable TOTCSR can be explained in terms of the three above-mentioned predictor variables.

Standard multiple regression was subsequently performed to examine the weighted linear combination of predictors a bit more thoroughly. The output of the standard multiple regression analysis differs slightly from that of the stepwise regression analysis due to a slight difference in the number of observations included in the analysis.

From the standard multiple regression analysis performed on the sub-sample of CSRs (Table B.2, Appendix B), it is evident that 10.85% ($R^2 = 0.1085$) of the variation in the dependent criterion variable can be explained in terms of the weighted linear combination of the following variables: CSHI, VERBHI, and TOTHI. The linear combination of predictors correlates statistically significantly ($p = 0.0056$) with the composite criterion. The significance of CSHI ($p = 0.0560$) and VERBHI ($p = 0.0947$) is borderline. TOTHI, however, significantly ($p = 0.0189$) explains unique variance in the composite criterion (TOTCSR).

It can furthermore be noted, when examining the regression coefficient parameter estimates, that CSHI seems to be the most influential predictor (parameter estimate = 19.215946). However, the parameter estimate can provide a misleading indication of the relative importance of a predictor in a regression model due to the fact that the predictors are not measured in the same units, and due to the fact that the predictors statistically overlap in terms of their individual contribution to the variance in the composite dependent criterion variable. To solve the problem of measurement in unequal units, the standardised estimate (β-value) is examined, from which it is evident, however, that TOTHI is in fact the most powerful predictor in terms of the average change in the criterion associated with one standard deviation change in the standardised predictor. To solve the problem of overlap, it is important to examine the Type II squared partial and semi-partial correlations.

Squared partial correlation refers to the proportion of unique criterion variance in the dependent variable explained by the unique variance in the independent variable. Thus, examining the most powerful predictor, approximately 4.95% (squared partial correlation = 0.04949087) of the variance in TOTCSR, which is not explained by the other predictors, is explained by the unique variance in TOTHI.

Squared semi-partial correlation refers to the proportion of the total variance in the dependent variable explained by the unique variance in the predictor not shared by the other independent variables. Examining TOTHI, approximately 4.64% (squared semi-partial correlation = 0.04641732) of the unique variance in TOTHI (in other words the variance in TOTHI not explained by any of the other predictors) can be associated with the total variance in the dependent variable, TOTCSR. Thus, only 4.64% of the TOTCSR variance can be explained in terms of the unique TOTHI variance.

7.5.3 Multiple Regression Analysis: PA

Variables were identified for inclusion in the stepwise regression analysis from the correlation matrix shown in Table A.3 in Appendix A. The list of predictor variables included in the stepwise regression analysis is shown in Table 7.7.

Table 7.7 Variables included in the PA stepwise regression analysis

1. CCSQHI	12. CCSQISEN
2. CCSQCOOP	13. CCSQPERS
3. CCSQPERF	14. CCSQSELF
4. CHECKHI	15. TOTEL
5. CLASSHI	16. TOTCOMM
7. TOTCOOP	17. CCSQCSO
8. TOTPERS	18. CCSQEL
9. NUMISP	19. CCSQISP
10. CCSQCOMM	20. CSPERS
11. TOTHI	21. VERBHI

The first eight variables were included due to their significant correlation with the composite criterion. Due to the high positive and significant ($p < 0.05$) correlation between them, the probability of inclusion of all these variables in a linear composite of predictors is practically zero. The remainder of the predictor variables were allowed to compete for inclusion in the predictor battery due to their significant correlation with the first eight predictors combined with their insignificant correlations with the composite criterion. The significance levels for entry into the model (SLE) and for staying in the model (SLS) were set at 0.15.

From the multiple stepwise regression analysis for the PA sub-sample shown in Table B.3 in Appendix B it is evident that, with the significance level liberally set at 0.1, TOTCOOP, CLASSHI, CCSQPERF, CCSQISEN and NUMISP have been identified as the predictors, from the entire list of predictors with which PAs were selected to statistically significantly ($p < 0.1$) explain unique variance in the overall dependent variable, TOTPA. Although the effect of CCSQISEN ($p = 0.0612$) and NUMISP ($p = 0.0616$) are borderline, each predictor significantly ($p < 0.1$) contributes to the variance in the composite criterion not explained by the other predictors included in the battery. No other individual predictor considered relevant to the selection of PAs could significantly explain additional variance in the composite criterion when added to the battery. Furthermore, it is disturbing that only approximately 22.28% ($R^2 = 0.22284603$) of the variation in the dependent variable TOTPA can be explained in terms of the weighted linear combination of TOTCOOP, CLASSHI, CCSQPERF, CCSQISEN and NUMISP.

Standard multiple regression was subsequently performed to examine the weighted linear combination of predictors a bit more thoroughly. The output of the standard multiple regression analysis differs slightly from that of the stepwise regression analysis due to a slight difference in the number of observations included in the analysis.

From the standard multiple regression analysis performed on the sub-sample of PAs (Table B.3, Appendix B), it is evident that 20.80% ($R^2 = 0.2080$) of the variation in the dependent criterion variable can be explained in terms of the weighted linear combination of the following variables: CLASSHI, CCSQPERF, TOTCOOP, CCSQISEN and NUMISP. The linear combination of predictors correlates statistically significantly ($p = 0.0001$) with the composite criterion. The significance of CLASSHI and CCSQISENS ($p = 0.0672$ and $p = 0.0545$) and CCSQPERF ($p = 0.0818$) is borderline, while NUMISP ($p = 0.1103$) does not significantly ($p > 0.05$) explain unique variance in the composite criterion in the standard multiple regression analysis.

When examining the regression coefficient parameter estimates, it further can be noted, that TOTCOOP seems to be the most influential predictor (parameter estimate = -22.951921). However, the parameter estimate can provide a misleading indication of the relative importance of a predictor in a regression model due to the fact that the predictors are not measured in the same units, and due to the fact that the predictors statistically overlap in terms of their individual contribution to the variance in the composite dependent criterion variable. To solve the problem of measurement in unequal units, the standardised estimate (β-value) is examined, which confirms

TOTCOOP to be the most powerful predictor in terms of the average change in the criterion associated with one standard deviation change in the standardised predictor. To solve the problem of overlap, it is important to examine the Type II squared partial and semi-partial correlations.

Squared partial correlation refers to the proportion of unique criterion variance in the dependent variable explained by the unique variance in the independent variable. Thus, examining the most powerful predictor, approximately 9.35 % (squared partial correlation = 0.09352218) of the variance in TOTPA, which is not explained by the other predictors, is explained by the unique variance in TOTCOOP.

Squared semi-partial correlation refers to the proportion of the total variance in the dependent variable explained by the unique variance in the predictor not shared by the other independent variables. Examining TOTCOOP, approximately 6.41% (squared semi-partial correlation = 0.06412605) of the unique variance in TOTCOOP (in other words the variance in TOTCOOP not explained by any of the other predictors) can be associated with the total variance in the dependent variable, TOTPA. Thus, 6.41 % of the TOTPA variance can be explained in terms of the unique TOTCOOP variance.

7.6 RESIDUALS

Where the linear regression strategy attempts to linearly combine the smallest number of predictors for the explanation of maximum variance in the criterion, the method of least squares calculates the regression coefficients so that the sum of the squared derivations of the Y values from the regression equation or the expected values are a minimum, that is the sum of the squared residuals must be a minimum.

The residuals (Y_i - $E[Y|X_i]$) have been plotted against the composite predictor and/or against the predicted performance, $E[Y|X_i]$ for each of the Coach, CSR and PA sub-samples separately, as well as each of the individual predictors included in the regression model.

The residual plots have been examined to evaluate the assumptions of normality, linearity and homoscedasticity. For each of the three groups, the residual plots indicate the assumptions of normality, linearity and homoscedasticity to be tenable.

7.7 CRITERION-REFERENCED NORM TABLES

From the appropriate regression equation, depending on the outcome of the fairness analysis, the calculation of a criterion-referenced norm table for each sub-sample is calculated. The norm table embodies the conviction that scores on the predictor battery should be interpreted criterion-referenced in terms of $E[Y|X_i]$ and/or $P[Y<Y_k|X_i]$. In the case of a battery of predictors, the calculation of a table predicting the expected level of criterion performance conditional on all possible combinations of predictor scores seems unrealistic. It does, however, make sense to develop a table depicting the probability of failure conditional on the weighted linear combination of predictor scores. Thus, the closer the probability value associated with a specific $E[Y|X_i]$ estimate graduates to 0, the greater the possibility of performance failure of that person when selected, i.e. the greater the risk of failure and the greater the risk of employing that individual. Conversely, the closer the probability value graduates to 1, the less the risk of failure and the greater the probability of success of a person being selected.

Criterion-references norm tables are used for the selection of candidates. They present a frame of reference for the purpose of selection decision-making by which a candidate can be compared to the rest of the candidates in terms of his/her expected performance on the criterion. Criterion-referenced norm tables have been calculated for the groups of the Coach, CSR, and PA respectively.

7.8 FAIRNESS ANALYSIS: THE CLEARY INTERPRETATION

The concept of fairness (fairness in relation to the type of analysis being performed in this study) comes to the fore when the administered selection instrument(s) discriminate negatively against members of one group (or sub-groups) in terms of which the applicant population can be differentiated. According to Cleary (1968), discrimination is prevalent if the performance of members of a certain group is statistically under-predicted and the performance of another group systematically over-predicted through the use of one single regression line developed on the two groups combined.

In the case of the sample used for this validation study, the fairness analysis should thus proceed in terms of the regression equations derived for the Coaches, CSRs, and PAs separately. However, as is evident from the position by race frequency table (Table 4.1), the largest group (CSR) is the only group with a significant number of black group members. Thus, the fairness analysis of the validation study only seems to be practically feasible in terms of the CSR sub-sample.

Two scatter plots were obtained as part of the statistical fairness analysis. The first scatter plot indicates the actual values of CSR members on the criterion against the composite predictor with group membership reflected by different plot symbols (see Figure C.1 in Appendix C). The minority group represents the different races of Asian, Black and Coloured (the so-called black group) and majority represents White (the so-called white group). The second scatter plot (see Figure C.2 in Appendix C) plots the standardised residuals against the composite predictor with group membership indicated by different plot symbols.

From a visual analysis of both scatter plots it appears that the use of a single regression line for group 0 (π_1) and group 1 (π_2) is fair, as the performance of π_1 and π_2 on the criterion does not appear to be systematically over-predicted or systematically under-predicted for either group. Moreover, when one examines the mean residuals of the two groups respectively, it is evident that the mean residual of the black group (μ = -0.02734084) is lower than the mean residual of the white group (μ = 0.01216132). Thus, the black group is slightly over-predicted and the white group is slightly under-predicted. This phenomenon, however, is not significant as the mean residuals of the two groups do not statistically significantly differ from each other ($p = 0.8502$).

Proceeding from the visual fairness analysis in terms of the scatter plots, the statistical analysis of fairness is necessary to confirm the derivations obtained from the visual analysis. In the examination of fairness of the current selection procedure in terms of the Cleary interpretation of fairness, two groups (π_1 = white; π_2 = black) are considered, and the linear regression of a composite criterion (TOTCSR) on a weighted linear combination of predictors (TOTHI, CSHI, VERBHI).

Given that the composite criterion (Y) has been regressed on the (composite) predictor (X) and the residuals ($Y_i - E[Y|X_i]$) have been computed and that the significance of the differences in mean residuals across the two groups have been tested by means of a t-test or a one-way Anova, the assumption of equal error variance across π_1 and π_2 can be tested by testing the following null hypothesis:

$$H_{01}: \sigma^2[Y|X; \pi_1] = \sigma^2[Y|X; \pi_2]$$

$$H_{a1}: \sigma^2[Y|X; \pi_1] \neq \sigma^2[Y|X; \pi_2]$$

by calculating the following test statistic (assuming $S^2[Y|X; \pi_1] > S^2[Y|X; \pi_2]$):

$$F = S^2[Y|X; \pi_1]/S[Y|X; \pi_2]$$

$$F = 4194.2413/3695.45616$$

$$F = 1.1349726$$

$$F \cong 1.13$$

The critical F-value is read off from an F table:

$$F[77; 32] \cong 1.69$$

Since $F = 1.13 < F = 1.69$, H_{01} cannot be rejected, and equal error variance can be assumed. The following saturated model is consequently fitted on the data by testing H_{02}:

$$E[YX] = \alpha + \beta_1[X] + \beta_2[D] + \beta_3[X^*D]$$

where $D = 0$ if group $= \pi_1$;

$D = 1$ if group $= \pi_2$.

The saturated model is consequently fitted by testing H_{02}:

$$H_{02}: \beta_2 = \beta_3 = 0|\beta_1 \neq 0$$

$$H_{a2}: \beta_2 \neq \beta_3 \neq 0| \beta_1 \neq 0$$

H_{02} is tested by calculating the following test statistic:

$$F = ([SSR[b_1, b_2, b_3] - SSR[b_1]/[p-1])/MSE[b_1, b_2, b_3]$$

$$F = ([57633.83165 - 54134.969]/2)/4047.80896$$

$$F = 0.432192$$

$$F \cong 0.43$$

The critical F-value is read off from an F table:

$$F[2;\ 109] \cong 3.09$$

Since F = 0.43 < F = 3.09, H_{02} cannot be rejected, implying that the regression equations for π_1 and π_2 do coincide and do not significantly differ in terms of slope and/or intercept. Thus, the use the regression equation fitted in the combined group as the basis of the decision rule will be fair to members of both groups.

Table C.10 in Appendix C, however, suggests the presence of a single group validity - possibly due to the size of the black group – which makes the use of a specific battery for the specific group difficult to justify.

7.9 UTILITY ANALYSIS

No utility analysis has been performed primarily due to the lack of a suitable estimate of the standard deviation of the composite criterion scaled in Rands and cents.

CHAPTER VIII

RECOMMENDATIONS FOR THE IMPROVEMENT OF THE EXISTING SELECTION APPROACH USED IN THE DEVELOPMENT AND JUSTIFICATION OF THE CALL CENTRE SELECTION PROCEDURE

8.1 OBJECTIVES OF THE STUDY

In the light of the introduction presented in Chapter I and the relevant psychometric literature reviewed in Chapter III with only the Guidelines (Society for Industrial Psychology, 1998) and the relevant labour legislation as a frame of reference, the objective of this study is the initiation of a comprehensive psychometric audit of the current personnel selection procedure for the selection of Call Centre staff at a South African insurance company.

A detailed overview of the objective of the comprehensive psychometric audit entails the following:

- To identify substantive and/or procedural shortcomings of the current selection procedure;
- To introduce suggestions regarding the correction of substantial shortcomings;
- To introduce and illustrate/apply suggestions regarding procedural modifications/corrections; and
- To develop an illustrative case study/norm in terms of which other current and future selection procedures can be evaluated.

8.2 RESEARCH METHODOLOGY

A psychometric audit implies the existence of an explicitly described ideal approach to the development and justification of a selection procedure that can serve as a template to guide the examination of the actual procedure used in the development and justification of the Call Centre selection procedure in an attempt to achieve greater organisational efficiency and to ensure the equitable utilisation of its human resources.

A literature study lays the required theoretical foundations for the development of such a template. In the context of this thesis, the literature study encapsulates the ideal procedure, a blueprint on which the practical execution of a validation study should be based on, with the Guidelines (1998) and the relevant labour legislation as a frame of reference.

A step by step comparison of the actual Call Centre selection procedure and its developmental history, and the ideal approach (encapsulated by the literature study) to the development and justification of a selection procedure constitute the essence of the psychometric audit. A checklist, representing a summary of the theoretical ideal derived through the literature study in terms of which any personnel selection procedure should be validated if the validation of a selection procedure is to be executed comprehensively, precisely and fairly, has been developed as a guide in comparing and summarising the nature and the extent to which the actual selection procedure conforms to the ideal procedure set out in the Guidelines (1998).

The checklist was followed by a detailed, systematic description of the developmental history and the composition of the selection procedure under investigation. The positions under investigation are described, followed by detailed descriptions of the following aspects, as necessities in a validation study:

- Job Analysis;
- Description of Predictor Variables; and
- Validation Sample.

Such a comparison uncovered serious substantive and procedural shortcomings. The audit has performed those phases of the ideal procedure that were neglected in the development and justification of the Call Centre selection procedure and/or indicated substantive deficiencies in the performance hypothesis.

A summary of the existing selection procedure and recommendations for procedural and substantive improvements follows. The empirical research findings obtained from the statistical analyses undertaken to rectify some of the procedural shortcomings are subsequently summarised.

8.3 SUMMARY OF THE RESEARCH FINDINGS

8.3.1 Job Analysis

The job analysis seems to have proceeded successfully. The job analysis was performed systematically and thoroughly and was administered on a valid and representative sample. The job analysis technique utilised is reasonably well known. A formal job description has been compiled and documented. No formal, written description on how exactly the job analysis was conducted has, however, been compiled.

8.3.2 Predictor Development

The psychometric tests that were used as predictors were well standardised, although it is not clear whether these predictor measures have been examined for differential item functioning or item bias. The case study and the role play that were developed by the first external consultant were not validated prior to their use. Furthermore, the manner in which the observed behaviour of the case study and role play have been rated is questionable. No concrete information is readily available as to how the elicited candidate behaviour has been judged. The objectivity of the case study and the role play assessment thus seem somewhat suspect.

8.3.3 Criterion Development

No formal constitutive definition of the final criterion seems to have been developed. Operational criterion measures have been developed to assess the criterion construct. No evidence exists to suggest that the operational criterion measures have been qualitatively evaluated in terms of criterion contamination, relevance, deficiency or reliability.

The questionnaire has never been psychometrically evaluated in the form it was originally developed and in its revised form in which it is to be used for the validation of the Call Centre selection procedure. The questionnaire has not been item analysed empirically, nor has it been examined empirically for differential items functioning. Neither has the reliability or the factorial or construct validity of the criterion measures been determined. As a result, no evidence exists that the performance measurements do in fact provide reliable and valid measures of the criterion construct.

The dependency of the received incentives on irrelevant, situational factors is a further contentious issue. A key assumption in selection validation research is that the criterion, against which the selection procedure is being evaluated, is an unbiased (i.e. uncontaminated by systematic measurement error) measure of the criterion construct. This is, however, apparently not the case.

8.3.4 Validation and Sampling

The term "applicant population" has not in any way been formally defined by The Company. Neither has the selection design been formally considered during the selection of the validation sample. Because the validation sample contains only individuals who have passed the first and the second assessment phases, the validation sample constitutes a too homogenous group (unless both phases are totally invalid) to permit the simple transportation of validation study findings on relevance, efficiençy and equity to the actual operation of the selection procedure. The sample size, seemingly not having been affected by statistical power considerations, had not been calculated *a priori* to achieve a specific, derived level of power in subsequent statistical analyses.

8.3.5 Data Capturing

For the purpose of a subsequent validation study, data from both geographically differentiated Call Centres was obtained. The data was obtained separately, but intended for the same purpose. However, there is insufficient information to rate the specifics of the activities regarding the data capturing process. It is not known how the data has been captured and to what extent standardised procedures were adhered to. Complete sets of criterion and predictor data have not been obtained for all cases initially. The reason for this is unknown. Appropriate strategies to replace missing data need to be developed.

8.3.6 Data Screening

The critical behaviours that must be executed when validating a selection procedure as mentioned in the checklist under "data screening" in Chapter VI have not been adhered to.

8.3.7 Data Analysis

No statistical analyses have been performed by The Company. The Company has, however, outsourced the requisite statistical analyses to the second external consultant. The Company's failure to perform the requisite statistical analyses necessarily means that no actuarially derived decision-rule exists to dictate, on the basis of the actual (not clinically presumed) relationships that exist between the composite criterion and the individual predictors, the manner in which various pieces of predictor information should be combined for selection decision-making.

8.3.8 Item and Reliability Analysis

The reliability of the questionnaires has been quantitatively evaluated in terms of each of the different sub-scales on each of the questionnaires developed for the CSR, PA and Coach. The Alpha coefficients (α) for each sub-scale for each of the three questionnaires are illustrated in Table 7.1.

8.3.9 Correlation Analysis

All possible inter-criterion, inter-predictor and predictor-criterion correlations have been calculated for each of the three Call Centre positions. In all three cases (COACH, CSR and PA) the inter-criterion correlations are very high. This should be regarded as problematic, since it would suggest the presence of a single underlying performance factor that is in all probability not in accordance with the implicit constitutive definition of the criterion construct.

Significant predictor-criterion correlations for all three groups are few and far between. Nine out of the 29 predictors for Coaches correlate significantly ($p < 0.05$) with one of the eight behavioural performance measure sub-scales, with only two predictors (RPACHOR and TOTACHOR) correlating significantly ($p < 0.05$) with the composite behavioural performance measure (TOTCOACH). No predictors correlate significantly ($p < 0.05$) with the incentive performance measure. The inter-predictor correlations present a more positive picture.

Three of the 35 predictors correlate significantly ($p < 0.05$) with the combined performance measure for CSRs. Together with CSPERS, VERBHI, CHECKHI and TOTPERS, the CSHI, CLASSHI and TOTHI predictors also correlate with the incentive measure for CSR performance. The inter-predictor correlations look slightly more promising.

The correlations for PAs look the most promising. Eight of 29 predictors correlate with the combined behavioural performance measure for PAs, while six correlate with the incentive measure of PA performance. CCSQCOOP and TOTCOOP correlate with all eight behavioural performance sub-scales.

8.3.10 Multiple Regression Analysis

From the multiple regression analysis performed on the sub-sample of Coaches, five predictor variables were identified for inclusion. TOTACHOR, OPQDECEX, OPQACHOR, VERBANAL and OPQDEMP each significantly ($p < 0.1$) and uniquely contribute to the variance in the composite criterion not explained by the other predictors included in the battery, with the SLE and SLS values both increased to 0.15.

45.21% ($R^2 = 0.4521$) of the variation in the dependent criterion variable can be explained in terms of the weighted linear combination of the following variables: TOTACHOR, OPQDECEX, OPQACHOR, VERBANAL and OPQEMP.

OPQDECEX is the most powerful predictor in terms of the average change in the criterion associated with one standard deviation change in the standardised predictor for the Coach sub-sample. Approximately 27.50% (squared partial correlation = 0.27496080) of the variance in TOTCOACH, which is not explained by the other predictors, is explained by the unique variance in OPQDECEX.

Approximately 20.78% (squared semi-partial correlation = 0.20776807) of the unique variance in OPQDECEX (in other words the variance in OPQDECEX not explained by any of the other predictors) can be associated with the total variance in the dependent variable, TOTCOACH.

From the multiple stepwise regression analysis for the CSR sub-sample shown in Table B.2 in Appendix B, it is evident that TOTHI, CSHI and VERBHI have been identified as the predictors, from the entire list of predictors with which CSRs were selected, to contribute statistically significantly ($p < 0.1$) ($p = 0.016$, $p = 0.0735$, $p = 0.0674$ respectively) to the overall dependent variable, TOTCSR. The significance levels for entry into the model (SLE) and for staying in the model (SLS) were set at 0.15.

From the standard multiple regression analysis performed on the sub-sample of CSRs (Table B.2, Appendix B), it is evident that only 10.85% ($R^2 = 0.1085$) of the variation in the dependent criterion variable can be explained in terms of the weighted linear combination of the following variables: CSHI, VERBHI, and TOTHI.

Examining TOTHI, the most powerful predictor, approximately 4.95% (squared partial correlation = 0.04949087) of the variance in TOTCSR, which is not explained by the other predictors, is explained by the unique variance in TOTHI. Approximately 4.64% (squared semi-partial correlation = 0.04641732) of the unique variance in TOTHI (in other words the variance in TOTHI not explained by any of the other predictors) can be associated with the total variance in the dependent variable, TOTCSR.

From the multiple stepwise regression analysis for the PA sub-sample shown in Table B.3 in Appendix B, it is evident that TOTCOOP, CLASSHI, CCSQPERF, CCSQISEN and NUMISP have been identified as the predictors, from the entire list of predictors with which PAs were selected that statistically significantly ($p < 0.1$) explain variance in the overall dependent variable, TOTPA.

Furthermore, it is disturbing that only approximately 22.28% ($R^2 = 0.22284603$) of the variation in the dependent variable TOTPA can be explained in terms of TOTCOOP, CLASSHI, CCSQPERF, CCSQISEN and NUMISP.

Approximately 9.35% (squared partial correlation = 0.09352218) of the variance in TOTPA, which is not explained by the other predictors, is explained by the unique variance in TOTCOOP, whereas approximately 6.41% (squared semi-partial correlation = 0.06412605) of the unique variance in TOTCOOP (in other words the variance in TOTCOOP not explained by any of the other predictors) can be associated with the total variance in the dependent variable, TOTPA.

8.4 RECOMMENDATIONS

The following section will highlight possible areas of improvement, implied by the procedural and/or substantive shortcomings identified by the psychometric audit, that The Company should seriously consider in its quest for a valid, reliable and fair selection procedure. The nature of the shortcomings seem to preclude the possibility of salvaging the current selection procedure by performing a few additional statistical analyses on the existing data set. What seems to be required is a comprehensive restoration of the whole developmental process. The specific recommendations are as follows:

- Develop an explicit performance hypothesis which explains variance in the latent criterion variable dimensions in terms of latent predictor variables;
- Depict the performance hypothesis in the form of a structural model utilising conventional LISREL notation;
- Argue the nature of the performance hypothesis in terms of the job description;
- Justify the inclusion of latent predictor variables in the structural model in terms of an empirical, logical and theoretical foundation;
- Document the performance hypothesis and its supporting argument on paper;
- Define all predictor and criterion constructs in the performance hypothesis through formal constitutive definitions;
- Integrate the endogenous and exogenous measurement models with the structural model to create a comprehensive LISREL model that clearly specifies how latent variables should express themselves in operational measures and how latent variables are related;
- Document the job analysis procedure thoroughly;
- Document the job description thoroughly;
- Evaluate the operational criterion measure in terms of criterion contamination, deficiency, relevance and reliability;
- Item analyse the criterion questionnaires and each predictor used;

- Evaluate empirically the predictor measures and the criterion questionnaire for differential item functioning or item bias;
- Revise the criterion questionnaires and psychometrically evaluate them in terms of reliability and validity and document the evidence accurately;
- Compile and document psychometric evidence on reliability and construct/factorial validity of all predictors;
- Explicitly define the applicant population and the validation design;
- Evaluate the internal and external validity of the validation design and assess the need for statistical corrections for restrictions of range and/or attenuation;
- Calculate the required sample size and the statistical power;
- Obtain complete sets of criterion and predictor data for all cases initially selected into the validation sample under standardised conditions;
- Rectify the problem of missing values, if applicable;
- Conduct a correlation analysis in terms of all possible predictor-criterion, inter-predictor and inter-criterion correlations and document the relevant evidence (correlations and statistical significance);
- Interpret predictor-criterion, inter-predictor and inter-criterion correlations in terms of the previously developed structural model;
- Correct the validity coefficient for the attenuating effect of criterion unreliability if necessary, depending on the reliability of the criterion measures;
- Correct for restriction of range if necessary, depending on the external validity of the validation design;
- Conduct a stepwise multiple regression analysis to assist in the identification of the predictors for their inclusion in the selection battery, and document the relevant evidence;
- Conduct a standard multiple regression analysis to determine the weighted linear combination of predictors, and document the evidence;
- Calculate the squared partial and semi-partial correlations to assess the relative importance of predictors in the regression model;
- Calculate a criterion-referenced norm table;
- Derive, describe and document explicit, formal decision-rules;
- Evaluate the fairness of the decision-rules and document the evidence; and
- Evaluate the utility of the decision-rule and document the evidence.

8.5 CONCLUDING REMARKS

The procedure for the selection of Call Centre staff was audited to identify procedural and substantive shortcomings because of the realisation that both drastic and subtle shortcomings in the development of the selection procedure can have an impact on the efficiency and the equity of the selection of quality employees. It is thus highly commendable that The Company had decided to validate the current selection procedure of Call Centre staff by outsourcing this complex task to an external consultant. It is from the above perspective that The Company is urged to seriously consider the results obtained, and the recommendations made, from the psychometric audit.

Generating the evidence to fully justify human resource interventions such as selection procedures is a reasonably complex, extensive and time-consuming exercise. If, however, the human resource function is serious in its ambition to justify itself to its stakeholders, it should devote the necessary resources such as personnel, time and money to the evaluation of its interventions. This seems to be an appropriate time for the creation of a specialised human resources audit function alongside the existing, more traditional human resource functions.

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APPENDIX A

CORRELATION MATRICES

Table A.1
Correlation matrix: Coach

Correlation Analysis

39 'VAR' Variables: TOTCOACH PERFMEAS INTSENS TEAMWORK ACHIEVE DECISIVE ANALYSIS DECISION GOALSET DEVEMP RPANAL RPCSO RPACHOR RPDECEX RPDEMP RPISEN RPOSMC CSANAL CSDEC OPQANAL OPQDEC OPQCSO OPQACHOR OPQDECEX OPQDEMP OPQTEAM OPQISEN OPQOSMC VERBANAL NUMANAL TOTANAL TOTDEC TOTCSO TOTACHOR TOTDECEX TOTDEMP TOTTEAM TOTISEN TOTOSMC

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
TOTCOACH	41	449.073171	135.861582	18412	31.000000	600.000000
PERFMEAS	41	70.785610	12.549707	2902.210000	42.000000	92.990000
INTSENS	38	55.078947	8.289953	2093.000000	38.000000	69.000000
TEAMWORK	41	68.634146	11.999492	2814.000000	31.000000	79.000000
ACHIEVE	38	49.447368	8.538300	1879.000000	29.000000	65.000000
DECISIVE	38	40.315789	5.292040	1532.000000	28.000000	50.000000
ANALYSIS	38	101.447368	17.273159	3855.000000	47.000000	133.000000
DECISION	38	54.894737	9.508999	2086.000000	22.000000	74.000000
GOALSET	38	48.421053	7.656940	1840.000000	26.000000	60.000000
DEVEMP	38	60.868421	12.997237	2313.000000	22.000000	81.000000
RPANAL	41	2.878049	0.899864	118.000000	1.000000	5.000000
RPCSO	41	3.439024	0.895790	141.000000	2.000000	5.000000
RPACHOR	41	3.512195	0.596739	144.000000	2.000000	5.000000
RPDECEX	41	3.024390	0.611874	124.000000	2.000000	4.000000
RPDEMP	41	3.390244	0.737497	139.000000	2.000000	5.000000
RPISEN	41	3.365854	0.829340	138.000000	2.000000	5.000000
RPOSMC	41	2.658537	0.656116	109.000000	2.000000	4.000000
CSANAL	41	2.390244	0.702782	98.000000	1.000000	4.000000
CSDEC	41	2.146341	0.691411	88.000000	1.000000	4.000000
OPQANAL	41	2.487805	0.675350	102.000000	2.000000	4.000000
OPQDEC	40	2.425000	0.500641	97.000000	2.000000	3.000000
OPQCSO	41	3.073171	0.647698	126.000000	1.000000	4.000000
OPQACHOR	41	2.707317	0.782429	111.000000	1.000000	4.000000
OPQDECEX	41	2.804878	0.641074	115.000000	2.000000	4.000000
OPQDEMP	41	2.634146	0.487652	108.000000	2.000000	3.000000
OPQTEAM	41	2.658537	0.574881	109.000000	1.000000	4.000000
OPQISEN	41	2.951220	0.312348	121.000000	2.000000	4.000000
OPQOSMC	41	2.585366	0.706244	106.000000	1.000000	4.000000
VERBANAL	40	29.750000	24.145658	1190.000000	1.000000	79.000000
NUMANAL	40	24.100000	18.850015	964.000000	1.000000	73.000000
TOTANAL	41	2.658537	0.728346	109.000000	1.000000	4.000000
TOTDEC	41	2.121951	0.640122	87.000000	1.000000	4.000000
TOTCSO	41	3.439024	0.867432	141.000000	2.000000	5.000000
TOTACHOR	41	3.463415	0.552158	142.000000	2.000000	4.000000
TOTDECEX	41	3.024390	0.611874	124.000000	2.000000	4.000000
TOTDEMP	41	3.317073	0.722462	136.000000	2.000000	5.000000
TOTTEAM	41	2.682927	0.567407	110.000000	1.000000	4.000000
TOTISEN	41	3.268293	0.742442	134.000000	2.000000	5.000000
TOTOSMC	40	2.675000	0.655842	107.000000	2.000000	4.000000

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCOACH	PERFMEAS	INTSENS	TEAMWORK	ACHIEVE	DECISIVE	ANALYSIS	DECISION	GOALSET	DEVEMP
TOTCOACH	1.00000	0.11686	0.80983	0.97426	0.86298	0.87648	0.96208	0.93655	0.91255	0.92920
	0.0	0.4669	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	41	41	38	41	38	38	38	38	38	38
PERFMEAS	0.11686	1.00000	0.21953	0.03497	0.23650	0.25297	0.15490	0.15355	0.20035	0.18039
	0.4669	0.0	0.1854	0.8282	0.1528	0.1254	0.3531	0.3574	0.2278	0.2785
	41	41	38	41	38	38	38	38	38	38
INTSENS	0.80983	0.21953	1.00000	0.78573	0.71810	0.65121	0.66526	0.78868	0.58364	0.73506
	0.0001	0.1854	0.0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	38	38	38	38	38	38	38	38	38	38
TEAMWORK	0.97426	0.03497	0.78573	1.00000	0.74351	0.80541	0.82564	0.85155	0.71861	0.75607
	0.0001	0.8282	0.0001	0.0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	41	41	38	41	38	38	38	38	38	38
ACHIEVE	0.86298	0.23650	0.71810	0.74351	1.00000	0.88503	0.76644	0.71929	0.78788	0.72801
	0.0001	0.1528	0.0001	0.0001	0.0	0.0001	0.0001	0.0001	0.0001	0.0001
	38	38	38	38	38	38	38	38	38	38
DECISIVE	0.87648	0.25297	0.65121	0.80541	0.88503	1.00000	0.82687	0.79502	0.78701	0.70830
	0.0001	0.1254	0.0001	0.0001	0.0001	0.0	0.0001	0.0001	0.0001	0.0001
	38	38	38	38	38	38	38	38	38	38
ANALYSIS	0.96208	0.15490	0.66526	0.82564	0.76644	0.82687	1.00000	0.91699	0.91484	0.89413
	0.0001	0.3531	0.0001	0.0001	0.0001	0.0001	0.0	0.0001	0.0001	0.0001
	38	38	38	38	38	38	38	38	38	38
DECISION	0.93655	0.15355	0.78868	0.85155	0.71929	0.79502	0.91699	1.00000	0.79685	0.83306
	0.0001	0.3574	0.0001	0.0001	0.0001	0.0001	0.0001	0.0	0.0001	0.0001
	38	38	38	38	38	38	38	38	38	38
GOALSET	0.91255	0.20035	0.58364	0.71861	0.78788	0.78701	0.91484	0.79685	1.00000	0.88537
	0.0001	0.2278	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0	0.0001
	38	38	38	38	38	38	38	38	38	38
DEVEMP	0.92920	0.18039	0.73506	0.75607	0.72801	0.70830	0.89413	0.83306	0.88537	1.00000
	0.0001	0.2785	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0
	38	38	38	38	38	38	38	38	38	38
RPANAL	-0.09133	-0.16621	-0.22899	-0.06212	-0.15647	-0.06441	-0.07734	-0.07698	-0.04636	-0.15766
	0.5701	0.2990	0.1667	0.6996	0.3482	0.7008	0.6444	0.6460	0.7822	0.3445
	41	41	38	41	38	38	38	38	38	38
RPCSO	0.12729	0.09180	-0.03330	0.09207	0.02384	0.06266	0.04232	0.04590	0.03988	-0.04426
	0.4277	0.5681	0.8427	0.5670	0.8870	0.7086	0.8008	0.7844	0.8121	0.7919
	41	41	38	41	38	38	38	38	38	38
RPACHOR	0.33656	0.07151	0.09939	0.32010	0.15575	0.26626	0.31624	0.27498	0.29425	0.20654
	0.0314	0.6568	0.5527	0.0413	0.3504	0.1061	0.0531	0.0948	0.0729	0.2134
	41	41	38	41	38	38	38	38	38	38

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCOACH	PERFMEAS	INTSENS	TEAMWORK	ACHIEVE	DECISIVE	ANALYSIS	DECISION	GOALSET	DEVEMP
RPDECEX	0.10463	-0.11260	0.29680	0.09659	0.30361	0.40683	0.57487	0.49441	0.47628	0.40566
	0.5150	0.4833	0.0704	0.5480	0.0639	0.0113	0.0002	0.0016	0.0025	0.0115
	41	41	38	41	38	38	38	38	38	38
RPDEMP	-0.03847	-0.15291	-0.04824	-0.08516	0.06215	0.12642	0.18500	0.14191	0.16040	0.09376
	0.8113	0.3399	0.7737	0.5965	0.7109	0.4494	0.2662	0.3954	0.3361	0.5755
	41	41	38	41	38	38	38	38	38	38
RPISEN	-0.14335	-0.24204	-0.17328	-0.11182	-0.28703	-0.12121	0.00034	-0.03567	-0.13531	-0.11363
	0.3712	0.1274	0.2981	0.4864	0.0806	0.4685	0.9984	0.8316	0.4180	0.4970
	41	41	38	41	38	38	38	38	38	38
RPOSMC	0.02076	0.00804	0.21796	-0.01626	0.16075	0.27570	0.30674	0.29711	0.32905	0.36418
	0.8975	0.9602	0.1887	0.9196	0.3350	0.0939	0.0610	0.0701	0.0437	0.0246
	41	41	38	41	38	38	38	38	38	38
CSANAL	0.05232	0.11398	0.02186	0.02921	0.04977	0.00187	0.11829	0.07354	0.02303	0.07521
	0.7453	0.4780	0.8963	0.8561	0.7667	0.9911	0.4794	0.6608	0.8909	0.6536
	41	41	38	41	38	38	38	38	38	38
CSDEC	-0.06239	0.16433	-0.10833	-0.09885	0.09335	0.08284	0.04614	0.01424	0.07968	-0.06008
	0.6984	0.3046	0.5174	0.5386	0.5772	0.6210	0.7833	0.9324	0.6344	0.7201
	41	41	38	41	38	38	38	38	38	38
OPQANAL	0.07535	-0.05287	-0.18777	0.09661	-0.20243	-0.18071	-0.21390	-0.19809	-0.25384	-0.17057
	0.6396	0.7427	0.2589	0.5479	0.2229	0.2776	0.1972	0.2332	0.1241	0.3059
	41	41	38	41	38	38	38	38	38	38
OPQDEC	0.16388	0.01745	-0.15962	0.14952	-0.03372	-0.18237	-0.09223	-0.13189	-0.05203	-0.05516
	0.3123	0.9149	0.3453	0.3571	0.8429	0.2800	0.5872	0.4365	0.7598	0.7457
	40	40	37	40	37	37	37	37	37	37
OPQCSO	-0.15064	-0.12031	-0.26685	-0.13157	-0.24739	-0.19694	-0.04569	-0.00830	0.05275	-0.12466
	0.3472	0.4537	0.1053	0.4122	0.1343	0.2360	0.7853	0.9606	0.7531	0.4559
	41	41	38	41	38	38	38	38	38	38
OPQACHOR	0.07311	0.20765	-0.17218	0.05222	-0.12043	-0.12594	-0.07683	-0.06699	-0.01849	-0.08426
	0.6496	0.1927	0.3013	0.7458	0.4714	0.4512	0.6466	0.6894	0.9123	0.6150
	41	41	38	41	38	38	38	38	38	38
OPQDECEX	-0.27223	0.24895	-0.23931	-0.29225	-0.17162	-0.10529	-0.08218	-0.10578	-0.07308	-0.19458
	0.0851	0.1165	0.1479	0.0637	0.3029	0.5293	0.6238	0.5274	0.6628	0.2417
	41	41	38	41	38	38	38	38	38	38
OPQDEMP	0.18946	-0.01183	-0.29796	0.23717	-0.29991	-0.30585	-0.25786	-0.26707	-0.26936	-0.26741
	0.2355	0.9415	0.0692	0.1354	0.0673	0.0618	0.1181	0.1050	0.1020	0.1046
	41	41	38	41	38	38	38	38	38	38
OPQTEAM	0.02305	-0.23307	-0.19893	0.01405	-0.21286	-0.20634	-0.23868	-0.19921	-0.28846	-0.21928
	0.8862	0.1425	0.2312	0.9305	0.1995	0.2139	0.1490	0.2305	0.0790	0.1859
	41	41	38	41	38	38	38	38	38	38

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCOACH	PERFMEAS	INTSENS	TEAMWORK	ACHIEVE	DECISIVE	ANALYSIS	DECISION	GOALSET	DEVEMP
OPQISEN	0.00480	0.11079	0.04178	0.03514	0.01849	0.05717	0.11524	0.14708	0.11796	0.01113
	0.9762	0.4905	0.8033	0.8273	0.9123	0.7332	0.4909	0.3782	0.4806	0.9471
	41	41	38	41	38	38	38	38	38	38
OPQOSMC	-0.16669	0.08418	-0.36480	-0.17470	-0.25375	-0.26859	-0.27072	-0.34146	-0.12359	-0.19339
	0.2976	0.6008	0.0243	0.2746	0.1242	0.1030	0.1002	0.0359	0.4598	0.2447
	41	41	38	41	38	38	38	38	38	38
VERBANAL	-0.12698	-0.14778	-0.29622	-0.10824	-0.35066	-0.27422	-0.31520	-0.35148	-0.25969	-0.23255
	0.4349	0.3628	0.0750	0.5061	0.0333	0.1005	0.0574	0.0329	0.1206	0.1660
	40	40	37	40	37	37	37	37	37	37
NUMANAL	-0.05590	-0.26446	-0.31232	-0.02963	-0.20611	-0.20889	-0.24413	-0.35274	-0.17474	-0.22199
	0.7319	0.0991	0.0598	0.8560	0.2210	0.2147	0.1453	0.0322	0.3010	0.1867
	40	40	37	40	37	37	37	37	37	37
TOTANAL	-0.08311	-0.11720	-0.21860	-0.06328	-0.23013	-0.17744	-0.12425	-0.16539	-0.07353	-0.13591
	0.6054	0.4655	0.1873	0.6943	0.1645	0.2865	0.4573	0.3210	0.6609	0.4159
	41	41	38	41	38	38	38	38	38	38
TOTDEC	-0.05903	0.16613	-0.08700	-0.09820	0.13274	0.12386	0.08249	0.04565	0.12683	-0.02716
	0.7139	0.2992	0.6035	0.5413	0.4269	0.4588	0.6225	0.7855	0.4480	0.8714
	41	41	38	41	38	38	38	38	38	38
TOTCSO	0.14461	0.10040	0.00577	0.11429	0.07429	0.08764	0.05951	0.06972	0.04912	-0.02943
	0.3670	0.5322	0.9726	0.4768	0.6576	0.6008	0.7226	0.6774	0.7696	0.8608
	41	41	38	41	38	38	38	38	38	38
TOTACHOR	0.36712	0.14054	0.17251	0.34318	0.22427	0.32978	0.36065	0.33648	0.36089	0.31145
	0.0182	0.3808	0.3003	0.0280	0.1759	0.0432	0.0261	0.0389	0.0260	0.0570
	41	41	38	41	38	38	38	38	38	38
TOTDECEX	0.10463	-0.11260	0.29680	0.09659	0.30361	0.40683	0.57487	0.49441	0.47628	0.40566
	0.5150	0.4833	0.0704	0.5480	0.0639	0.0113	0.0002	0.0016	0.0025	0.0115
	41	41	38	41	38	38	38	38	38	38
TOTDEMP	-0.07309	-0.15086	-0.06178	-0.11894	0.02197	0.07346	0.16480	0.12490	0.18024	0.10356
	0.6497	0.3464	0.7125	0.4589	0.8958	0.6612	0.3228	0.4550	0.2789	0.5361
	41	41	38	41	38	38	38	38	38	38
TOTTEAM	0.01393	-0.22331	-0.23730	0.00457	-0.25251	-0.24877	-0.27987	-0.23719	-0.33959	-0.26659
	0.9311	0.1605	0.1514	0.9774	0.1262	0.1321	0.0888	0.1516	0.0370	0.1057
	41	41	38	41	38	38	38	38	38	38
TOTISEN	-0.17567	-0.11640	-0.11595	-0.15147	-0.29094	-0.12133	-0.01047	-0.02291	-0.10241	-0.04933
	0.2719	0.4686	0.4882	0.3445	0.0764	0.4681	0.9502	0.8914	0.5407	0.7687
	41	41	38	41	38	38	38	38	38	38
TOTOSMC	0.01547	0.01575	0.20289	-0.02221	0.14402	0.26007	0.29253	0.28380	0.31172	0.34873
	0.9245	0.9231	0.2285	0.8918	0.3951	0.1201	0.0789	0.0887	0.0604	0.0344
	40	40	37	40	37	37	37	37	37	37

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	RPANAL	RPCSO	RPACHOR	RPDECEX	RPDEMP	RPISEN	RPOSMC	CSANAL	CSDEC	OPQANAL
TOTCOACH	-0.09133	0.12729	0.33656	0.10463	-0.03847	-0.14335	0.02076	0.05232	-0.06239	0.07535
	0.5701	0.4277	0.0314	0.5150	0.8113	0.3712	0.8975	0.7453	0.6984	0.6396
	41	41	41	41	41	41	41	41	41	41
PERFMEAS	-0.16621	0.09180	0.07151	-0.11260	-0.15291	-0.24204	0.00804	0.11398	0.16433	-0.05287
	0.2990	0.5681	0.6568	0.4833	0.3399	0.1274	0.9602	0.4780	0.3046	0.7427
	41	41	41	41	41	41	41	41	41	41
INTSENS	-0.22899	-0.03330	0.09939	0.29680	-0.04824	-0.17328	0.21796	0.02186	-0.10833	-0.18777
	0.1667	0.8427	0.5527	0.0704	0.7737	0.2981	0.1887	0.8963	0.5174	0.2589
	38	38	38	38	38	38	38	38	38	38
TEAMWORK	-0.06212	0.09207	0.32010	0.09659	-0.08516	-0.11182	-0.01626	0.02921	-0.09885	0.09661
	0.6996	0.5670	0.0413	0.5480	0.5965	0.4864	0.9196	0.8561	0.5386	0.5479
	41	41	41	41	41	41	41	41	41	41
ACHIEVE	-0.15647	0.02384	0.15575	0.30361	0.06215	-0.28703	0.16075	0.04977	0.09335	-0.20243
	0.3482	0.8870	0.3504	0.0639	0.7109	0.0806	0.3350	0.7667	0.5772	0.2229
	38	38	38	38	38	38	38	38	38	38
DECISIVE	-0.06441	0.06266	0.26626	0.40683	0.12642	-0.12121	0.27570	0.00187	0.08284	-0.18071
	0.7008	0.7086	0.1061	0.0113	0.4494	0.4685	0.0939	0.9911	0.6210	0.2776
	38	38	38	38	38	38	38	38	38	38
ANALYSIS	-0.07734	0.04232	0.31624	0.57487	0.18500	0.00034	0.30674	0.11829	0.04614	-0.21390
	0.6444	0.8008	0.0531	0.0002	0.2662	0.9984	0.0610	0.4794	0.7833	0.1972
	38	38	38	38	38	38	38	38	38	38
DECISION	-0.07698	0.04590	0.27498	0.49441	0.14191	-0.03567	0.29711	0.07354	0.01424	-0.19809
	0.6460	0.7844	0.0948	0.0016	0.3954	0.8316	0.0701	0.6608	0.9324	0.2332
	38	38	38	38	38	38	38	38	38	38
GOALSET	-0.04636	0.03988	0.29425	0.47628	0.16040	-0.13531	0.32905	0.02303	0.07968	-0.25384
	0.7822	0.8121	0.0729	0.0025	0.3361	0.4180	0.0437	0.8909	0.6344	0.1241
	38	38	38	38	38	38	38	38	38	38
DEVEMP	-0.15766	-0.04426	0.20654	0.40566	0.09376	-0.11363	0.36418	0.07521	-0.06008	-0.17057
	0.3445	0.7919	0.2134	0.0115	0.5755	0.4970	0.0246	0.6536	0.7201	0.3059
	38	38	38	38	38	38	38	38	38	38
RPANAL	1.00000	0.13011	0.21234	0.27797	0.63856	0.53026	0.09708	0.11667	0.02940	0.01806
	0.0	0.4175	0.1826	0.0785	0.0001	0.0004	0.5460	0.4676	0.8552	0.9108
	41	41	41	41	41	41	41	41	41	41
RPCSO	0.13011	1.00000	0.45741	0.07120	0.18829	0.11491	0.30397	-0.04068	-0.02560	0.05040
	0.4175	0.0	0.0026	0.6582	0.2384	0.4744	0.0533	0.8006	0.8738	0.7544
	41	41	41	41	41	41	41	41	41	41
RPACHOR	0.21234	0.45741	1.00000	0.44421	0.32975	0.16756	0.33016	-0.01163	0.11675	0.23300
	0.1826	0.0026	0.0	0.0036	0.0353	0.2950	0.0350	0.9425	0.4673	0.1426
	41	41	41	41	41	41	41	41	41	41

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	RPANAL	RPCSO	RPACHOR	RPDECEX	RPDEMP	RPISEN	RPOSMC	CSANAL	CSDEC	OPQANAL
RPDECEX	0.27797	0.07120	0.44421	1.00000	0.25538	0.32684	0.33263	0.20986	0.22773	0.03099
	0.0785	0.6582	0.0036	0.0	0.1071	0.0370	0.0336	0.1879	0.1522	0.8475
	41	41	41	41	41	41	41	41	41	41
RPDEMP	0.63856	0.18829	0.32975	0.25538	1.00000	0.41472	-0.02772	0.18117	0.17937	-0.04040
	0.0001	0.2384	0.0353	0.1071	0.0	0.0070	0.8634	0.2570	0.2618	0.8020
	41	41	41	41	41	41	41	41	41	41
RPISEN	0.53026	0.11491	0.16756	0.32684	0.41472	1.00000	0.05155	0.13496	-0.00851	-0.01415
	0.0004	0.4744	0.2950	0.0370	0.0070	0.0	0.7489	0.4002	0.9579	0.9300
	41	41	41	41	41	41	41	41	41	41
RPOSMC	0.09708	0.30397	0.33016	0.33263	-0.02772	0.05155	1.00000	0.07934	0.11291	0.10321
	0.5460	0.0533	0.0350	0.0336	0.8634	0.7489	0.0	0.6219	0.4821	0.5208
	41	41	41	41	41	41	41	41	41	41
CSANAL	0.11667	-0.04068	-0.01163	0.20986	0.18117	0.13496	0.07934	1.00000	0.70273	-0.09507
	0.4676	0.8006	0.9425	0.1879	0.2570	0.4002	0.6219	0.0	0.0001	0.5544
	41	41	41	41	41	41	41	41	41	41
CSDEC	0.02940	-0.02560	0.11675	0.22773	0.17937	-0.00851	0.11291	0.70273	1.00000	-0.15670
	0.8552	0.8738	0.4673	0.1522	0.2618	0.9579	0.4821	0.0001	0.0	0.3279
	41	41	41	41	41	41	41	41	41	41
OPQANAL	0.01806	0.05040	0.23300	0.03099	-0.04040	-0.01415	0.10321	-0.09507	-0.15670	1.00000
	0.9108	0.7544	0.1426	0.8475	0.8020	0.9300	0.5208	0.5544	0.3279	0.0
	41	41	41	41	41	41	41	41	41	41
OPQDEC	-0.04323	0.07645	0.00642	-0.17097	0.05574	-0.17700	-0.31326	0.23119	0.25249	0.22066
	0.7911	0.6392	0.9687	0.2915	0.7326	0.2746	0.0490	0.1512	0.1160	0.1712
	40	40	40	40	40	40	40	40	40	40
OPQCSO	0.23016	0.02943	-0.09939	0.12155	-0.06127	0.08854	-0.11622	-0.17414	-0.13616	-0.08364
	0.1477	0.8551	0.5364	0.4490	0.7035	0.5820	0.4693	0.2762	0.3960	0.6031
	41	41	41	41	41	41	41	41	41	41
OPQACHOR	-0.01645	0.08091	-0.20634	-0.14137	-0.31701	-0.17760	-0.10215	-0.19627	-0.33476	0.04039
	0.9187	0.6151	0.1955	0.3779	0.0434	0.2666	0.5251	0.2187	0.0324	0.8020
	41	41	41	41	41	41	41	41	41	41
OPQDECEX	0.04439	0.10937	-0.12432	0.01244	-0.15218	-0.00344	-0.16236	-0.21519	-0.27238	-0.00563
	0.7829	0.4961	0.4387	0.9385	0.3422	0.9830	0.3105	0.1766	0.0849	0.9721
	41	41	41	41	41	41	41	41	41	41
OPQDEMP	0.18064	-0.08096	0.14458	-0.13692	-0.01017	0.15378	-0.16580	0.13522	0.16276	0.40362
	0.2584	0.6148	0.3671	0.3933	0.9497	0.3371	0.3002	0.3993	0.3093	0.0089
	41	41	41	41	41	41	41	41	41	41
OPQTEAM	0.01414	0.15274	0.01244	-0.04680	0.08629	0.11127	0.08083	0.09055	0.12886	0.31097
	0.9301	0.3404	0.9385	0.7714	0.5916	0.4886	0.6154	0.5734	0.4220	0.0478
	41	41	41	41	41	41	41	41	41	41

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	RPANAL	RPCSO	RPACHOR	RPDECEX	RPDEMP	RPISEN	RPOSMC	CSANAL	CSDEC	OPQANAL
OPQISEN	0.06725	-0.10025	0.27153	0.13719	0.19323	0.07062	-0.20530	0.08889	0.14964	-0.00289
	0.6761	0.5329	0.0859	0.3924	0.2261	0.6609	0.1979	0.5805	0.3504	0.9857
	41	41	41	41	41	41	41	41	41	41
OPQOSMC	-0.08155	0.05783	-0.07668	-0.20742	-0.25755	-0.28941	-0.04342	-0.37101	-0.23101	0.17259
	0.6122	0.7195	0.6337	0.1932	0.1040	0.0665	0.7875	0.0169	0.1462	0.2806
	41	41	41	41	41	41	41	41	41	41
VERBANAL	-0.00834	0.06282	0.22574	-0.03368	0.04511	0.02621	0.02486	0.09887	0.21472	0.27647
	0.9592	0.7002	0.1613	0.8366	0.7822	0.8724	0.8790	0.5439	0.1833	0.0842
	40	40	40	40	40	40	40	40	40	40
NUMANAL	0.03848	0.09054	0.04749	-0.14076	-0.08730	0.27434	-0.09984	-0.19303	-0.11585	0.10239
	0.8136	0.5785	0.7710	0.3863	0.5922	0.0867	0.5399	0.2327	0.4766	0.5296
	40	40	40	40	40	40	40	40	40	40
TOTANAL	0.77404	0.04392	0.23990	0.29964	0.48698	0.46031	0.06380	0.46220	0.30029	0.14380
	0.0001	0.7851	0.1308	0.0570	0.0012	0.0025	0.6919	0.0023	0.0564	0.3697
	41	41	41	41	41	41	41	41	41	41
TOTDEC	0.06987	-0.00851	0.09418	0.24753	0.21441	0.00804	0.16115	0.66958	0.97542	-0.19888
	0.6643	0.9579	0.5581	0.1187	0.1783	0.9602	0.3141	0.0001	0.0001	0.2126
	41	41	41	41	41	41	41	41	41	41
TOTCSO	0.10233	0.96834	0.47237	0.07353	0.19444	0.08391	0.22606	0.04001	0.05693	0.00937
	0.5243	0.0001	0.0018	0.6478	0.2231	0.6019	0.1553	0.8039	0.7237	0.9536
	41	41	41	41	41	41	41	41	41	41
TOTACHOR	0.21721	0.43764	0.93084	0.40969	0.34290	0.11185	0.37870	-0.09114	0.01437	0.25018
	0.1725	0.0042	0.0001	0.0078	0.0282	0.4863	0.0146	0.5709	0.9289	0.1147
	41	41	41	41	41	41	41	41	41	41
TOTDECEX	0.27797	0.07120	0.44421	1.00000	0.25538	0.32684	0.33263	0.20986	0.22773	0.03099
	0.0785	0.6582	0.0036	0.0001	0.1071	0.0370	0.0336	0.1879	0.1522	0.8475
	41	41	41	41	41	41	41	41	41	41
TOTDEMP	0.59933	0.12719	0.25175	0.15173	0.93498	0.42742	0.02315	0.04564	0.05493	-0.11997
	0.0001	0.4281	0.1123	0.3436	0.0001	0.0053	0.8857	0.7769	0.7330	0.4550
	41	41	41	41	41	41	41	41	41	41
TOTTEAM	-0.02866	0.13316	0.04862	-0.04918	0.06411	0.09330	0.03767	0.19267	0.24868	0.34848
	0.8588	0.4065	0.7627	0.7601	0.6904	0.5618	0.8151	0.2275	0.1169	0.0256
	41	41	41	41	41	41	41	41	41	41
TOTISEN	0.49923	0.08160	0.07707	0.26040	0.35190	0.93285	0.14145	0.03389	-0.07840	-0.11796
	0.0009	0.6120	0.6320	0.1001	0.0241	0.0001	0.3777	0.8334	0.6261	0.4626
	41	41	41	41	41	41	41	41	41	41
TOTOSMC	0.07384	0.29612	0.35889	0.33597	-0.04203	0.04083	1.00000	0.15056	0.20400	0.12525
	0.6507	0.0636	0.0230	0.0340	0.7968	0.8025	0.0001	0.3538	0.2067	0.4412
	40	40	40	40	40	40	40	40	40	40

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	OPQDEC	OPQCSO	OPQACHOR	OPQDECEX	OPQDEMP	OPQTEAM	OPQISEN	OPQOSMC	VERBANAL	NUMANAL
TOTCOACH	0.16388	-0.15064	0.07311	-0.27223	0.18946	0.02305	0.00480	-0.16669	-0.12698	-0.05590
	0.3123	0.3472	0.6496	0.0851	0.2355	0.8862	0.9762	0.2976	0.4349	0.7319
	40	41	41	41	41	41	41	41	40	40
PERFMEAS	0.01745	-0.12031	0.20765	0.24895	-0.01183	-0.23307	0.11079	0.08418	-0.14778	-0.26446
	0.9149	0.4537	0.1927	0.1165	0.9415	0.1425	0.4905	0.6008	0.3628	0.0991
	40	41	41	41	41	41	41	41	40	40
INTSENS	-0.15962	-0.26685	-0.17218	-0.23931	-0.29796	-0.19893	0.04178	-0.36480	-0.29622	-0.31232
	0.3453	0.1053	0.3013	0.1479	0.0692	0.2312	0.8033	0.0243	0.0750	0.0598
	37	38	38	38	38	38	38	38	37	37
TEAMWORK	0.14952	-0.13157	0.05222	-0.29225	0.23717	0.01405	0.03514	-0.17470	-0.10824	-0.02963
	0.3571	0.4122	0.7458	0.0637	0.1354	0.9305	0.8273	0.2746	0.5061	0.8560
	40	41	41	41	41	41	41	41	40	40
ACHIEVE	-0.03372	-0.24739	-0.12043	-0.17162	-0.29991	-0.21286	0.01849	-0.25375	-0.35066	-0.20611
	0.8429	0.1343	0.4714	0.3029	0.0673	0.1995	0.9123	0.1242	0.0333	0.2210
	37	38	38	38	38	38	38	38	37	37
DECISIVE	-0.18237	-0.19694	-0.12594	-0.10529	-0.30585	-0.20634	0.05717	-0.26859	-0.27422	-0.20889
	0.2800	0.2360	0.4512	0.5293	0.0618	0.2139	0.7332	0.1030	0.1005	0.2147
	37	38	38	38	38	38	38	38	37	37
ANALYSIS	-0.09223	-0.04569	-0.07683	-0.08218	-0.25786	-0.23868	0.11524	-0.27072	-0.31520	-0.24413
	0.5872	0.7853	0.6466	0.6238	0.1181	0.1490	0.4909	0.1002	0.0574	0.1453
	37	38	38	38	38	38	38	38	37	37
DECISION	-0.13189	-0.00830	-0.06699	-0.10578	-0.26707	-0.19921	0.14708	-0.34146	-0.35148	-0.35274
	0.4365	0.9606	0.6894	0.5274	0.1050	0.2305	0.3782	0.0359	0.0329	0.0322
	37	38	38	38	38	38	38	38	37	37
GOALSET	-0.05203	0.05275	-0.01849	-0.07308	-0.26936	-0.28846	0.11796	-0.12359	-0.25969	-0.17474
	0.7598	0.7531	0.9123	0.6628	0.1020	0.0790	0.4806	0.4598	0.1206	0.3010
	37	38	38	38	38	38	38	38	37	37
DEVEMP	-0.05516	-0.12466	-0.08426	-0.19458	-0.26741	-0.21928	0.01113	-0.19339	-0.23255	-0.22199
	0.7457	0.4559	0.6150	0.2417	0.1046	0.1859	0.9471	0.2447	0.1660	0.1867
	37	38	38	38	38	38	38	38	37	37
RPANAL	-0.04323	0.23016	-0.01645	0.04439	0.18064	0.01414	0.06725	-0.08155	-0.00834	0.03848
	0.7911	0.1477	0.9187	0.7829	0.2584	0.9301	0.6761	0.6122	0.9592	0.8136
	40	41	41	41	41	41	41	41	40	40
RPCSO	0.07645	0.02943	0.08091	0.10937	-0.08096	0.15274	-0.10025	0.05783	0.06282	0.09054
	0.6392	0.8551	0.6151	0.4961	0.6148	0.3404	0.5329	0.7195	0.7002	0.5785
	40	41	41	41	41	41	41	41	40	40
RPACHOR	0.00642	-0.09939	-0.20634	-0.12432	0.14458	0.01244	0.27153	-0.07668	0.22574	0.04749
	0.9687	0.5364	0.1955	0.4387	0.3671	0.9385	0.0859	0.6337	0.1613	0.7710
	40	41	41	41	41	41	41	41	40	40

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	OPQDEC	OPQCSO	OPQACHOR	OPQDECEX	OPQDEMP	OPQTEAM	OPQISEN	OPQOSMC	VERBANAL	NUMANAL
RPDECEX	-0.17097	0.12155	-0.14137	0.01244	-0.13692	-0.04680	0.13719	-0.20742	-0.03368	-0.14076
	0.2915	0.4490	0.3779	0.9385	0.3933	0.7714	0.3924	0.1932	0.8366	0.3863
	40	41	41	41	41	41	41	41	40	40
RPDEMP	0.05574	-0.06127	-0.31701	-0.15218	-0.01017	0.08629	0.19323	-0.25755	0.04511	-0.08730
	0.7326	0.7035	0.0434	0.3422	0.9497	0.5916	0.2261	0.1040	0.7822	0.5922
	40	41	41	41	41	41	41	41	40	40
RPISEN	-0.17700	0.08854	-0.17760	-0.00344	0.15378	0.11127	0.07062	-0.28941	0.02621	0.27434
	0.2746	0.5820	0.2666	0.9830	0.3371	0.4886	0.6609	0.0665	0.8724	0.0867
	40	41	41	41	41	41	41	41	40	40
RPOSMC	-0.31326	-0.11622	-0.10215	-0.16236	-0.16580	0.08083	-0.20530	-0.04342	0.02486	-0.09984
	0.0490	0.4693	0.5251	0.3105	0.3002	0.6154	0.1979	0.7875	0.8790	0.5399
	40	41	41	41	41	41	41	41	40	40
CSANAL	0.23119	-0.17414	-0.19627	-0.21519	0.13522	0.09055	0.08889	-0.37101	0.09887	-0.19303
	0.1512	0.2762	0.2187	0.1766	0.3993	0.5734	0.5805	0.0169	0.5439	0.2327
	40	41	41	41	41	41	41	41	40	40
CSDEC	0.25249	-0.13616	-0.33476	-0.27238	0.16276	0.12886	0.14964	-0.23101	0.21472	-0.11585
	0.1160	0.3960	0.0324	0.0849	0.3093	0.4220	0.3504	0.1462	0.1833	0.4766
	40	41	41	41	41	41	41	41	40	40
OPQANAL	0.22066	-0.08364	0.04039	-0.00563	0.40362	0.31097	-0.00289	0.17259	0.27647	0.10239
	0.1712	0.6031	0.8020	0.9721	0.0089	0.0478	0.9857	0.2806	0.0842	0.5296
	40	41	41	41	41	41	41	41	40	40
OPQDEC	1.00000	0.05662	0.07123	-0.12637	0.41881	0.08395	-0.02429	0.08811	0.20628	0.23448
	0.0	0.7286	0.6623	0.4372	0.0072	0.6065	0.8817	0.5888	0.2016	0.1453
	40	40	40	40	40	40	40	40	40	40
OPQCSO	0.05662	1.00000	0.48730	0.57712	0.08687	-0.19979	0.26523	0.39590	-0.21900	-0.00270
	0.7286	0.0	0.0012	0.0001	0.5891	0.2104	0.0937	0.0104	0.1746	0.9868
	40	41	41	41	41	41	41	41	40	40
OPQACHOR	0.07123	0.48730	1.00000	0.63091	-0.09109	-0.11658	-0.26447	0.31780	-0.18527	0.01410
	0.6623	0.0012	0.0	0.0001	0.5711	0.4679	0.0947	0.0429	0.2524	0.9312
	40	41	41	41	41	41	41	41	40	40
OPQDECEX	-0.12637	0.57712	0.63091	1.00000	-0.07412	-0.25314	0.07613	0.20336	-0.30459	-0.18292
	0.4372	0.0001	0.0001	0.0	0.6451	0.1103	0.6362	0.2022	0.0560	0.2586
	40	41	41	41	41	41	41	41	40	40
OPQDEMP	0.41881	0.08687	-0.09109	-0.07412	1.00000	0.25666	0.04404	0.05666	0.17038	0.12503
	0.0072	0.5891	0.5711	0.6451	0.0	0.1053	0.7846	0.7250	0.2932	0.4421
	40	41	41	41	41	41	41	41	40	40
OPQTEAM	0.08395	-0.19979	-0.11658	-0.25314	0.25666	1.00000	-0.09508	0.19674	0.24644	0.32014
	0.6065	0.2104	0.4679	0.1103	0.1053	0.0	0.5543	0.2176	0.1253	0.0440
	40	41	41	41	41	41	41	41	40	40

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	OPQDEC	OPQCSO	OPQACHOR	OPQDECEX	OPQDEMP	OPQTEAM	OPQISEN	OPQOSMC	VERBANAL	NUMANAL
OPQISEN	-0.02429	0.26523	-0.26447	0.07613	0.04404	-0.09508	1.00000	0.13268	0.00168	0.00516
	0.8817	0.0937	0.0947	0.6362	0.7846	0.5543	0.0	0.4083	0.9918	0.9748
	40	41	41	41	41	41	41	41	40	40
OPQOSMC	0.08811	0.39590	0.31780	0.20336	0.05666	0.19674	0.13268	1.00000	0.16218	0.32035
	0.5888	0.0104	0.0429	0.2022	0.7250	0.2176	0.4083	0.0	0.3174	0.0439
	40	41	41	41	41	41	41	41	40	40
VERBANAL	0.20628	-0.21900	-0.18527	-0.30459	0.17038	0.24644	0.00168	0.16218	1.00000	0.57502
	0.2016	0.1746	0.2524	0.0560	0.2932	0.1253	0.9918	0.3174	0.0	0.0001
	40	40	40	40	40	40	40	40	40	40
NUMANAL	0.23448	-0.00270	0.01410	-0.18292	0.12503	0.32014	0.00516	0.32035	0.57502	1.00000
	0.1453	0.9868	0.9312	0.2586	0.4421	0.0440	0.9748	0.0439	0.0001	0.0
	40	40	40	40	40	40	40	40	40	40
TOTANAL	0.08202	0.10728	-0.17976	-0.09272	0.27296	-0.04660	0.14474	-0.18492	0.23964	-0.02733
	0.6149	0.5044	0.2608	0.5642	0.0842	0.7723	0.3666	0.2471	0.1364	0.8671
	40	41	41	41	41	41	41	41	40	40
TOTDEC	0.22724	-0.08236	-0.27636	-0.24517	0.14650	0.18392	0.15553	-0.16185	0.15118	-0.09971
	0.1585	0.6087	0.0803	0.1223	0.3607	0.2497	0.3315	0.3120	0.3517	0.5404
	40	41	41	41	41	41	41	41	40	40
TOTCSO	0.13746	-0.01411	0.00988	0.06798	-0.08361	0.05747	-0.10352	-0.06271	0.09521	0.03449
	0.3976	0.9302	0.9511	0.6728	0.6033	0.7212	0.5195	0.6969	0.5590	0.8327
	40	41	41	41	41	41	41	41	40	40
TOTACHOR	-0.00693	-0.02728	-0.08327	-0.09130	0.08832	0.03842	0.27931	0.05629	0.14134	0.02725
	0.9661	0.8656	0.6047	0.5702	0.5829	0.8115	0.0770	0.7267	0.3843	0.8674
	40	41	41	41	41	41	41	41	40	40
TOTDECEX	-0.17097	0.12155	-0.14137	0.01244	-0.13692	-0.04680	0.13719	-0.20742	-0.03368	-0.14076
	0.2915	0.4490	0.3779	0.9385	0.3933	0.7714	0.3924	0.1932	0.8366	0.3863
	40	41	41	41	41	41	41	41	40	40
TOTDEMP	0.00366	0.00261	-0.27399	-0.13297	-0.01731	0.08662	0.18104	-0.17687	-0.09029	-0.04743
	0.9821	0.9871	0.0830	0.4072	0.9145	0.5902	0.2573	0.2686	0.5795	0.7714
	40	41	41	41	41	41	41	41	40	40
TOTTEAM	0.13647	-0.27542	-0.21426	-0.31179	0.29309	0.96270	-0.08945	0.10043	0.34094	0.29542
	0.4011	0.0814	0.1786	0.0472	0.0629	0.0001	0.5781	0.5321	0.0313	0.0642
	40	41	41	41	41	41	41	41	40	40
TOTISEN	-0.29034	0.11412	-0.11966	0.00769	0.07073	0.10286	0.05785	-0.16397	-0.07929	0.21215
	0.0692	0.4774	0.4562	0.9620	0.6603	0.5222	0.7194	0.3057	0.6267	0.1888
	40	41	41	41	41	41	41	41	40	40
TOTOSMC	-0.29239	-0.16691	-0.17113	-0.20132	-0.14951	0.05294	-0.20400	-0.10983	0.08320	-0.11856
	0.0709	0.3033	0.2910	0.2129	0.3571	0.7456	0.2067	0.4999	0.6146	0.4722
	39	40	40	40	40	40	40	40	39	39

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTANAL	TOTDEC	TOTCSO	TOTACHOR	TOTDECEX	TOTDEMP	TOTTEAM	TOTISEN	TOTOSMC
TOTCOACH	-0.08311	-0.05903	0.14461	0.36712	0.10463	-0.07309	0.01393	-0.17567	0.01547
	0.6054	0.7139	0.3670	0.0182	0.5150	0.6497	0.9311	0.2719	0.9245
	41	41	41	41	41	41	41	41	40
PERFMEAS	-0.11720	0.16613	0.10040	0.14054	-0.11260	-0.15086	-0.22331	-0.11640	0.01575
	0.4655	0.2992	0.5322	0.3808	0.4833	0.3464	0.1605	0.4686	0.9231
	41	41	41	41	41	41	41	41	40
INTSENS	-0.21860	-0.08700	0.00577	0.17251	0.29680	-0.06178	-0.23730	-0.11595	0.20289
	0.1873	0.6035	0.9726	0.3003	0.0704	0.7125	0.1514	0.4882	0.2285
	38	38	38	38	38	38	38	38	37
TEAMWORK	-0.06328	-0.09820	0.11429	0.34318	0.09659	-0.11894	0.00457	-0.15147	-0.02221
	0.6943	0.5413	0.4768	0.0280	0.5480	0.4589	0.9774	0.3445	0.8918
	41	41	41	41	41	41	41	41	40
ACHIEVE	-0.23013	0.13274	0.07429	0.22427	0.30361	0.02197	-0.25251	-0.29094	0.14402
	0.1645	0.4269	0.6576	0.1759	0.0639	0.8958	0.1262	0.0764	0.3951
	38	38	38	38	38	38	38	38	37
DECISIVE	-0.17744	0.12386	0.08764	0.32978	0.40683	0.07346	-0.24877	-0.12133	0.26007
	0.2865	0.4588	0.6008	0.0432	0.0113	0.6612	0.1321	0.4681	0.1201
	38	38	38	38	38	38	38	38	37
ANALYSIS	-0.12425	0.08249	0.05951	0.36065	0.57487	0.16480	-0.27987	-0.01047	0.29253
	0.4573	0.6225	0.7226	0.0261	0.0002	0.3228	0.0888	0.9502	0.0789
	38	38	38	38	38	38	38	38	37
DECISION	-0.16539	0.04565	0.06972	0.33648	0.49441	0.12490	-0.23719	-0.02291	0.28380
	0.3210	0.7855	0.6774	0.0389	0.0016	0.4550	0.1516	0.8914	0.0887
	38	38	38	38	38	38	38	38	37
GOALSET	-0.07353	0.12683	0.04912	0.36089	0.47628	0.18024	-0.33959	-0.10241	0.31172
	0.6609	0.4480	0.7696	0.0260	0.0025	0.2789	0.0370	0.5407	0.0604
	38	38	38	38	38	38	38	38	37
DEVEMP	-0.13591	-0.02716	-0.02943	0.31145	0.40566	0.10356	-0.26659	-0.04933	0.34873
	0.4159	0.8714	0.8608	0.0570	0.0115	0.5361	0.1057	0.7687	0.0344
	38	38	38	38	38	38	38	38	37
RPANAL	0.77404	0.06987	0.10233	0.21721	0.27797	0.59933	-0.02866	0.49923	0.07384
	0.0001	0.6643	0.5243	0.1725	0.0785	0.0001	0.8588	0.0009	0.6507
	41	41	41	41	41	41	41	41	40
RPCSO	0.04392	-0.00851	0.96834	0.43764	0.07120	0.12719	0.13316	0.08160	0.29612
	0.7851	0.9579	0.0001	0.0042	0.6582	0.4281	0.4065	0.6120	0.0636
	41	41	41	41	41	41	41	41	40
RPACHOR	0.23990	0.09418	0.47237	0.93084	0.44421	0.25175	0.04862	0.07707	0.35889
	0.1308	0.5581	0.0018	0.0001	0.0036	0.1123	0.7627	0.6320	0.0230
	41	41	41	41	41	41	41	41	40

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTANAL	TOTDEC	TOTCSO	TOTACHOR	TOTDECEX	TOTDEMP	TOTTEAM	TOTISEN	TOTOSMC
RPDECEX	0.29964	0.24753	0.07353	0.40969	1.00000	0.15173	-0.04918	0.26040	0.33597
	0.0570	0.1187	0.6478	0.0078	0.0001	0.3436	0.7601	0.1001	0.0340
	41	41	41	41	41	41	41	41	40
RPDEMP	0.48698	0.21441	0.19444	0.34290	0.25538	0.93498	0.06411	0.35190	-0.04203
	0.0012	0.1783	0.2231	0.0282	0.1071	0.0001	0.6904	0.0241	0.7968
	41	41	41	41	41	41	41	41	40
RPISEN	0.46031	0.00804	0.08391	0.11185	0.32684	0.42742	0.09330	0.93285	0.04083
	0.0025	0.9602	0.6019	0.4863	0.0370	0.0053	0.5618	0.0001	0.8025
	41	41	41	41	41	41	41	41	40
RPOSMC	0.06380	0.16115	0.22606	0.37870	0.33263	0.02315	0.03767	0.14145	1.00000
	0.6919	0.3141	0.1553	0.0146	0.0336	0.8857	0.8151	0.3777	0.0001
	41	41	41	41	41	41	41	41	40
CSANAL	0.46220	0.66958	0.04001	-0.09114	0.20986	0.04564	0.19267	0.03389	0.15056
	0.0023	0.0001	0.8039	0.5709	0.1879	0.7769	0.2275	0.8334	0.3538
	41	41	41	41	41	41	41	41	40
CSDEC	0.30029	0.97542	0.05693	0.01437	0.22773	0.05493	0.24868	-0.07840	0.20400
	0.0564	0.0001	0.7237	0.9289	0.1522	0.7330	0.1169	0.6261	0.2067
	41	41	41	41	41	41	41	41	40
OPQANAL	0.14380	-0.19888	0.00937	0.25018	0.03099	-0.11997	0.34848	-0.11796	0.12525
	0.3697	0.2126	0.9536	0.1147	0.8475	0.4550	0.0256	0.4626	0.4412
	41	41	41	41	41	41	41	41	40
OPQDEC	0.08202	0.22724	0.13746	-0.00693	-0.17097	0.00366	0.13647	-0.29034	-0.29239
	0.6149	0.1585	0.3976	0.9661	0.2915	0.9821	0.4011	0.0692	0.0709
	40	40	40	40	40	40	40	40	39
OPQCSO	0.10728	-0.08236	-0.01411	-0.02728	0.12155	0.00261	-0.27542	0.11412	-0.16691
	0.5044	0.6087	0.9302	0.8656	0.4490	0.9871	0.0814	0.4774	0.3033
	41	41	41	41	41	41	41	41	40
OPQACHOR	-0.17976	-0.27636	0.00988	-0.08327	-0.14137	-0.27399	-0.21426	-0.11966	-0.17113
	0.2608	0.0803	0.9511	0.6047	0.3779	0.0830	0.1786	0.4562	0.2910
	41	41	41	41	41	41	41	41	40
OPQDECEX	-0.09272	-0.24517	0.06798	-0.09130	0.01244	-0.13297	-0.31179	0.00769	-0.20132
	0.5642	0.1223	0.6728	0.5702	0.9385	0.4072	0.0472	0.9620	0.2129
	41	41	41	41	41	41	41	41	40
OPQDEMP	0.27296	0.14650	-0.08361	0.08832	-0.13692	-0.01731	0.29309	0.07073	-0.14951
	0.0842	0.3607	0.6033	0.5829	0.3933	0.9145	0.0629	0.6603	0.3571
	41	41	41	41	41	41	41	41	40
OPQTEAM	-0.04660	0.18392	0.05747	0.03842	-0.04680	0.08662	0.96270	0.10286	0.05294
	0.7723	0.2497	0.7212	0.8115	0.7714	0.5902	0.0001	0.5222	0.7456
	41	41	41	41	41	41	41	41	40

Table A.1
Correlation matrix: Coach

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTANAL	TOTDEC	TOTCSO	TOTACHOR	TOTDECEX	TOTDEMP	TOTTEAM	TOTISEN	TOTOSMC
OPQISEN	0.14474	0.15553	-0.10352	0.27931	0.13719	0.18104	-0.08945	0.05785	-0.20400
	0.3666	0.3315	0.5195	0.0770	0.3924	0.2573	0.5781	0.7194	0.2067
	41	41	41	41	41	41	41	41	40
OPQOSMC	-0.18492	-0.16185	-0.06271	0.05629	-0.20742	-0.17687	0.10043	-0.16397	-0.10983
	0.2471	0.3120	0.6969	0.7267	0.1932	0.2686	0.5321	0.3057	0.4999
	41	41	41	41	41	41	41	41	40
VERBANAL	0.23964	0.15118	0.09521	0.14134	-0.03368	-0.09029	0.34094	-0.07929	0.08320
	0.1364	0.3517	0.5590	0.3843	0.8366	0.5795	0.0313	0.6267	0.6146
	40	40	40	40	40	40	40	40	39
NUMANAL	-0.02733	-0.09971	0.03449	0.02725	-0.14076	-0.04743	0.29542	0.21215	-0.11856
	0.8671	0.5404	0.8327	0.8674	0.3863	0.7714	0.0642	0.1888	0.4722
	40	40	40	40	40	40	40	40	39
TOTANAL	1.00000	0.25241	0.08493	0.15465	0.29964	0.35343	0.03394	0.35858	0.11787
	0.0	0.1113	0.5975	0.3343	0.0570	0.0234	0.8332	0.0213	0.4688
	41	41	41	41	41	41	41	41	40
TOTDEC	0.25241	1.00000	0.03624	0.04830	0.24753	0.13053	0.24678	-0.01796	0.20400
	0.1113	0.0	0.8220	0.7642	0.1187	0.4160	0.1198	0.9112	0.2067
	41	41	41	41	41	41	41	41	40
TOTCSO	0.08493	0.03624	1.00000	0.39975	0.07353	0.09146	0.08672	0.00663	0.24722
	0.5975	0.8220	0.0	0.0096	0.6478	0.5695	0.5898	0.9672	0.1241
	41	41	41	41	41	41	41	41	40
TOTACHOR	0.15465	0.04830	0.39975	1.00000	0.40969	0.31182	0.00195	0.11602	0.36512
	0.3343	0.7642	0.0096	0.0	0.0078	0.0472	0.9904	0.4701	0.0205
	41	41	41	41	41	41	41	41	40
TOTDECEX	0.29964	0.24753	0.07353	0.40969	1.00000	0.15173	-0.04918	0.26040	0.33597
	0.0570	0.1187	0.6478	0.0078	0.0	0.3436	0.7601	0.1001	0.0340
	41	41	41	41	41	41	41	41	40
TOTDEMP	0.35343	0.13053	0.09146	0.31182	0.15173	1.00000	0.00744	0.44335	-0.02514
	0.0234	0.4160	0.5695	0.0472	0.3436	0.0	0.9632	0.0037	0.8776
	41	41	41	41	41	41	41	41	40
TOTTEAM	0.03394	0.24678	0.08672	0.00195	-0.04918	0.00744	1.00000	0.02895	0.05294
	0.8332	0.1198	0.5898	0.9904	0.7601	0.9632	0.0	0.8574	0.7456
	41	41	41	41	41	41	41	41	40
TOTISEN	0.35858	-0.01796	0.00663	0.11602	0.26040	0.44335	0.02895	1.00000	0.10271
	0.0213	0.9112	0.9672	0.4701	0.1001	0.0037	0.8574	0.0	0.5283
	41	41	41	41	41	41	41	41	40
TOTOSMC	0.11787	0.20400	0.24722	0.36512	0.33597	-0.02514	0.05294	0.10271	1.00000
	0.4688	0.2067	0.1241	0.0205	0.0340	0.8776	0.7456	0.5283	0.0
	40	40	40	40	40	40	40	40	40

Table A.2
Correlation matrix: Csr

Correlation Analysis

45 'VAR' Variables: TOTCSR PERFMEAS INSEN CLIENTSO COMMUNIC PERFOR PERSEVER SELFCONT EAGERNES IDENTSOL RPISP RPCSO RPCOMM RPISEN RPPERF RPSELF CSISP CSHI CSPERF CSPERS CCSQISP CCSQEL CCSQHI CCSQCSO CCSQCOMM CCSQISEN CCSQCOOP CCSQPERF CCSQPERS CCSQSELF VERBISP VERBHI CHECKHI CLASSHI NUMISP TOTISP TOTEL TOTHI TOTCSO TOTCOMM TOTISEN TOTCOOP TOTPERF TOTPERS TOTSELF

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
TOTCSR	114	340.991228	66.459316	38873	139.000000	473.000000
PERFMEAS	143	63.682937	19.256669	9106.660000	15.010000	101.220000
INSEN	114	45.026316	8.478458	5133.000000	21.000000	60.000000
CLIENTSO	114	51.789474	10.940283	5904.000000	17.000000	70.000000
COMMUNIC	114	66.657895	12.759747	7599.000000	26.000000	90.000000
PERFOR	106	23.235849	7.206547	2463.000000	3.000000	35.000000
PERSEVER	111	31.585586	7.026532	3506.000000	10.000000	45.000000
SELFCONT	114	24.157895	6.301536	2754.000000	9.000000	35.000000
EAGERNES	114	31.105263	9.350944	3546.000000	4.000000	45.000000
IDENTSOL	114	69.894737	13.929893	7968.000000	31.000000	100.000000
RPISP	147	2.843537	0.689458	418.000000	1.000000	5.000000
RPCSO	147	3.217687	0.567583	473.000000	2.000000	5.000000
RPCOMM	147	2.925170	0.620301	430.000000	2.000000	5.000000
RPISEN	147	3.190476	0.600609	469.000000	2.000000	5.000000
RPPERF	147	2.741497	0.741051	403.000000	1.000000	5.000000
RPSELF	147	3.238095	0.589094	476.000000	2.000000	5.000000
CSISP	147	1.775510	0.649509	261.000000	1.000000	4.000000
CSHI	147	1.557823	0.620751	229.000000	1.000000	3.000000
CSPERF	147	1.646259	0.738406	242.000000	1.000000	4.000000
CSPERS	147	1.435374	0.662788	211.000000	1.000000	4.000000
CCSQISP	146	3.342466	0.942765	488.000000	1.000000	5.000000
CCSQEL	146	3.616438	0.763479	528.000000	2.000000	5.000000
CCSQHI	146	3.698630	0.736907	540.000000	2.000000	5.000000
CCSQCSO	146	3.931507	0.767059	574.000000	2.000000	5.000000
CCSQCOMM	146	2.753425	0.986541	402.000000	1.000000	5.000000
CCSQISEN	146	3.712329	0.760752	542.000000	2.000000	5.000000
CCSQCOOP	146	3.773973	0.768075	551.000000	2.000000	5.000000
CCSQPERF	146	3.513699	0.754173	513.000000	1.000000	5.000000
CCSQPERS	146	3.075342	0.839422	449.000000	1.000000	5.000000
CCSQSELF	146	3.198630	0.859991	467.000000	1.000000	5.000000
VERBISP	147	34.598639	25.704501	5086.000000	1.000000	93.000000
VERBHI	145	29.096552	26.206531	4219.000000	1.000000	93.000000
CHECKHI	147	61.360544	23.746361	9020.000000	5.000000	99.000000
CLASSHI	147	49.285714	23.232299	7245.000000	5.000000	96.000000
NUMISP	147	45.401361	21.668948	6674.000000	3.000000	92.000000
TOTISP	147	2.884354	0.646561	424.000000	1.000000	5.000000
TOTEL	146	3.616438	0.763479	528.000000	2.000000	5.000000
TOTHI	147	3.346939	0.799427	492.000000	2.000000	5.000000
TOTCSO	147	3.244898	0.592092	477.000000	2.000000	5.000000
TOTCOMM	147	2.931973	0.615550	431.000000	2.000000	5.000000
TOTISEN	147	3.183673	0.597029	468.000000	2.000000	5.000000
TOTCOOP	146	3.767123	0.770500	550.000000	2.000000	5.000000
TOTPERF	147	2.632653	0.609082	387.000000	1.000000	5.000000
TOTPERS	147	1.482993	0.675944	218.000000	1.000000	4.000000
TOTSELF	147	3.238095	0.589094	476.000000	2.000000	5.000000

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCSR	PERFMEAS	INSEN	CLIENTSO	COMMUNIC	PERFOR	PERSEVER	SELFCONT	EAGERNES	IDENTSOL	RPISP	RPCSO
TOTCSR	1.00000	0.36703	0.79999	0.86270	0.92122	0.76443	0.87505	0.73496	0.76965	0.90555	0.01803	-0.00090
	0.0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.8490	0.9924
	114	113	114	114	114	106	111	114	114	114	114	114
PERFMEAS	0.36703	1.00000	0.23844	0.32518	0.40746	0.44675	0.38008	0.30826	0.23335	0.32370	-0.14348	0.04334
	0.0001	0.0	0.0110	0.0004	0.0001	0.0001	0.0001	0.0009	0.0129	0.0005	0.0873	0.6073
	113	143	113	113	113	105	110	113	113	113	143	143
INSEN	0.79999	0.23844	1.00000	0.73555	0.73049	0.41900	0.63233	0.61709	0.46755	0.69051	0.01212	-0.03846
	0.0001	0.0110	0.0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.8981	0.6845
	114	113	114	114	114	106	111	114	114	114	114	114
CLIENTSO	0.86270	0.32518	0.73555	1.00000	0.77505	0.57593	0.74106	0.56632	0.53153	0.76892	-0.00353	-0.03136
	0.0001	0.0004	0.0001	0.0	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.9702	0.7405
	114	113	114	114	114	106	111	114	114	114	114	114
COMMUNIC	0.92122	0.40746	0.73049	0.77505	1.00000	0.65979	0.76149	0.66842	0.65826	0.83187	0.00467	-0.05004
	0.0001	0.0001	0.0001	0.0001	0.0	0.0001	0.0001	0.0001	0.0001	0.0001	0.9607	0.5970
	114	113	114	114	114	106	111	114	114	114	114	114
PERFOR	0.76443	0.44675	0.41900	0.57593	0.65979	1.00000	0.71756	0.54257	0.66212	0.61555	-0.09448	0.03073
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0	0.0001	0.0001	0.0001	0.0001	0.3354	0.7545
	106	105	106	106	106	106	105	106	106	106	106	106
PERSEVER	0.87505	0.38008	0.63233	0.74106	0.76149	0.71756	1.00000	0.62796	0.69794	0.79174	-0.09387	0.00554
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0	0.0001	0.0001	0.0001	0.3271	0.9539
	111	110	111	111	111	105	111	111	111	111	111	111
SELFCONT	0.73496	0.30826	0.61709	0.56632	0.66842	0.54257	0.62796	1.00000	0.51394	0.61920	0.07650	-0.10758
	0.0001	0.0009	0.0001	0.0001	0.0001	0.0001	0.0001	0.0	0.0001	0.0001	0.4185	0.2546
	114	113	114	114	114	106	111	114	114	114	114	114
EAGERNES	0.76965	0.23335	0.46755	0.53153	0.65826	0.66212	0.69794	0.51394	1.00000	0.68083	0.05314	0.00906
	0.0001	0.0129	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0	0.0001	0.5745	0.9238
	114	113	114	114	114	106	111	114	114	114	114	114
IDENTSOL	0.90555	0.32370	0.69051	0.76892	0.83187	0.61555	0.79174	0.61920	0.68083	1.00000	0.09003	0.07097
	0.0001	0.0005	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0	0.3408	0.4530
	114	113	114	114	114	106	111	114	114	114	114	114
RPISP	0.01803	-0.14348	0.01212	-0.00353	0.00467	-0.09448	-0.09387	0.07650	0.05314	0.09003	1.00000	0.33267
	0.8490	0.0873	0.8981	0.9702	0.9607	0.3354	0.3271	0.4185	0.5745	0.3408	0.0	0.0001
	114	143	114	114	114	106	111	114	114	114	147	147
RPCSO	-0.00090	0.04334	-0.03846	-0.03136	-0.05004	0.03073	0.00554	-0.10758	0.00906	0.07097	0.33267	1.00000
	0.9924	0.6073	0.6845	0.7405	0.5970	0.7545	0.9539	0.2546	0.9238	0.4530	0.0001	0.0
	114	143	114	114	114	106	111	114	114	114	147	147
RPCOMM	0.09602	0.00973	0.07509	0.11785	0.09140	0.05093	0.08503	0.00461	-0.02692	0.11703	0.35681	0.24113
	0.3095	0.9082	0.4272	0.2118	0.3334	0.6041	0.3749	0.9612	0.7761	0.2150	0.0001	0.0033
	114	143	114	114	114	106	111	114	114	114	147	147

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCSR	PERFMEAS	INSEN	CLIENTSO	COMMUNIC	PERFOR	PERSEVER	SELFCONT	EAGERNES	IDENTSOL	RPISP	RPCSO
RPISEN	-0.11508	-0.09056	-0.05873	-0.12987	-0.13280	-0.17454	-0.09755	-0.07447	-0.05287	-0.06517	0.33711	0.29947
	0.2228	0.2821	0.5348	0.1685	0.1590	0.0735	0.3084	0.4310	0.5764	0.4909	0.0001	0.0002
	114	143	114	114	114	106	111	114	114	114	147	147
RPPERF	0.04090	0.02949	0.02082	0.13714	0.01004	0.06541	0.03203	-0.04975	0.01041	0.05642	0.38950	0.46039
	0.6657	0.7266	0.8260	0.1457	0.9155	0.5053	0.7386	0.5991	0.9124	0.5510	0.0001	0.0001
	114	143	114	114	114	106	111	114	114	114	147	147
RPSELF	0.04425	-0.00168	-0.04770	0.03693	0.03351	-0.05783	-0.00535	0.06184	0.03588	0.05309	0.19353	0.43799
	0.6402	0.9841	0.6143	0.6965	0.7234	0.5560	0.9556	0.5134	0.7047	0.5748	0.0188	0.0001
	114	143	114	114	114	106	111	114	114	114	147	147
CSISP	0.08166	0.10248	0.05639	0.05450	0.05320	0.23544	0.09565	-0.02493	0.06563	0.03826	0.10457	0.09631
	0.3877	0.2233	0.5512	0.5646	0.5740	0.0151	0.3180	0.7924	0.4878	0.6861	0.2075	0.2459
	114	143	114	114	114	106	111	114	114	114	147	147
CSHI	0.19391	0.18952	0.13226	0.09078	0.16470	0.25435	0.25589	0.14706	0.21910	0.12467	-0.01873	-0.03597
	0.0387	0.0234	0.1607	0.3368	0.0799	0.0085	0.0067	0.1184	0.0192	0.1863	0.8219	0.6653
	114	143	114	114	114	106	111	114	114	114	147	147
CSPERF	0.15986	0.14958	0.06233	0.18663	0.07193	0.20726	0.23247	0.07180	0.15666	0.09614	0.07889	0.10328
	0.0893	0.0746	0.5100	0.0468	0.4470	0.0330	0.0141	0.4478	0.0960	0.3089	0.3422	0.2132
	114	143	114	114	114	106	111	114	114	114	147	147
CSPERS	0.11506	0.17306	0.00583	0.16343	0.05922	0.19763	0.18543	-0.03536	0.13644	0.08042	0.00020	0.07407
	0.2228	0.0387	0.9509	0.0823	0.5314	0.0423	0.0514	0.7088	0.1478	0.3950	0.9980	0.3726
	114	143	114	114	114	106	111	114	114	114	147	147
CCSQISP	-0.06320	-0.00644	-0.10312	-0.11934	-0.00141	-0.05827	-0.03282	-0.04954	-0.01076	-0.01862	0.07273	0.05193
	0.5060	0.9393	0.2771	0.2080	0.9882	0.5549	0.7336	0.6023	0.9100	0.8448	0.3830	0.5336
	113	142	113	113	113	105	110	113	113	113	146	146
CCSQEL	-0.12866	-0.08356	-0.20729	-0.14972	-0.08756	-0.04775	-0.12518	-0.07202	-0.05888	-0.09007	0.06762	0.03608
	0.1744	0.3228	0.0276	0.1135	0.3564	0.6286	0.1926	0.4484	0.5356	0.3428	0.4174	0.6654
	113	142	113	113	113	105	110	113	113	113	146	146
CCSQHI	0.04060	-0.07216	0.01687	0.00798	0.08396	0.01088	0.05828	0.03179	0.09986	0.01627	0.08211	0.07635
	0.6694	0.3934	0.8592	0.9332	0.3766	0.9123	0.5453	0.7382	0.2926	0.8642	0.3245	0.3597
	113	142	113	113	113	105	110	113	113	113	146	146
CCSQCSO	0.07054	0.13188	0.01023	0.07233	0.10863	0.13845	0.11197	0.00000	0.07668	0.02131	-0.03347	0.12938
	0.4578	0.1177	0.9144	0.4464	0.2521	0.1590	0.2442	1.0000	0.4196	0.8228	0.6883	0.1196
	113	142	113	113	113	105	110	113	113	113	146	146
CCSQCOMM	-0.02230	-0.09606	0.04716	-0.02504	0.03130	-0.11817	0.01952	-0.04626	-0.04483	0.05338	0.12460	-0.05047
	0.8146	0.2554	0.6199	0.7923	0.7420	0.2299	0.8396	0.6266	0.6373	0.5744	0.1340	0.5452
	113	142	113	113	113	105	110	113	113	113	146	146
CCSQISEN	0.03701	-0.02261	0.09649	0.08950	0.12163	-0.07420	0.03759	0.06125	-0.09337	0.04750	-0.04740	-0.02858
	0.6971	0.7894	0.3093	0.3459	0.1994	0.4519	0.6966	0.5193	0.3253	0.6173	0.5700	0.7320
	113	142	113	113	113	105	110	113	113	113	146	146

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCSR	PERFMEAS	INSEN	CLIENTSO	COMMUNIC	PERFOR	PERSEVER	SELFCONT	EAGERNES	IDENTSOL	RPISP	RPCSO
CCSQCOOP	0.08624	-0.09664	0.10825	0.06110	0.09304	-0.00048	0.02637	0.10653	0.11166	0.09756	-0.01556	-0.10674
	0.3638	0.2526	0.2538	0.5203	0.3270	0.9961	0.7845	0.2614	0.2390	0.3039	0.8521	0.1997
	113	142	113	113	113	105	110	113	113	113	146	146
CCSQPERF	0.01433	0.00731	0.01646	-0.00636	0.09657	0.06483	0.07963	-0.01365	0.00563	-0.02753	0.06366	0.08934
	0.8803	0.9312	0.8626	0.9467	0.3089	0.5111	0.4083	0.8859	0.9528	0.7722	0.4453	0.2835
	113	142	113	113	113	105	110	113	113	113	146	146
CCSQPERS	0.07023	0.12279	0.05596	0.05443	0.11679	0.08153	0.12835	0.05794	0.04701	0.07877	0.04434	0.06623
	0.4598	0.1455	0.5560	0.5669	0.2180	0.4083	0.1814	0.5421	0.6210	0.4069	0.5951	0.4270
	113	142	113	113	113	105	110	113	113	113	146	146
CCSQSELF	0.04889	0.06305	0.00940	0.02631	0.09355	0.03812	0.04036	0.03317	-0.02344	0.08170	0.01818	0.02316
	0.6071	0.4560	0.9213	0.7821	0.3244	0.6995	0.6754	0.7273	0.8054	0.3896	0.8275	0.7814
	113	142	113	113	113	105	110	113	113	113	146	146
VERBISP	-0.07017	-0.04273	-0.09089	-0.10130	0.00821	0.00066	-0.13399	-0.08934	-0.10493	-0.03793	0.04397	0.01824
	0.4581	0.6123	0.3362	0.2835	0.9309	0.9946	0.1609	0.3445	0.2666	0.6887	0.5969	0.8265
	114	143	114	114	114	106	111	114	114	114	147	147
VERBHI	-0.14663	-0.32240	-0.15142	-0.19011	-0.06371	-0.15033	-0.12194	-0.05383	-0.15570	-0.11840	-0.01901	-0.00886
	0.1212	0.0001	0.1094	0.0437	0.5026	0.1258	0.2044	0.5712	0.0996	0.2116	0.8205	0.9158
	113	141	113	113	113	105	110	113	113	113	145	145
CHECKHI	0.15750	0.19055	0.07785	0.10076	0.18451	0.13784	0.12595	0.16398	0.05686	0.10452	0.05786	0.13744
	0.0942	0.0226	0.4103	0.2861	0.0494	0.1588	0.1878	0.0813	0.5479	0.2684	0.4864	0.0969
	114	143	114	114	114	106	111	114	114	114	147	147
CLASSHI	0.21637	0.22378	0.10136	0.19696	0.26668	0.12827	0.14567	0.13088	0.16601	0.20043	0.02248	0.08148
	0.0208	0.0072	0.2833	0.0357	0.0041	0.1901	0.1271	0.1652	0.0775	0.0325	0.7870	0.3266
	114	143	114	114	114	106	111	114	114	114	147	147
NUMISP	0.11919	0.06922	0.07214	0.09296	0.12609	0.17017	0.05857	0.16085	0.06643	0.05676	0.01019	-0.09236
	0.2066	0.4114	0.4456	0.3253	0.1813	0.0812	0.5415	0.0873	0.4825	0.5486	0.9025	0.2659
	114	143	114	114	114	106	111	114	114	114	147	147
TOTISP	0.05168	-0.13249	0.12554	0.03893	0.01031	-0.11186	-0.09322	0.04930	0.07228	0.13528	0.88103	0.31170
	0.5850	0.1147	0.1832	0.6809	0.9133	0.2536	0.3305	0.6024	0.4448	0.1513	0.0001	0.0001
	114	143	114	114	114	106	111	114	114	114	147	147
TOTEL	-0.12866	-0.08356	-0.20729	-0.14972	-0.08756	-0.04775	-0.12518	-0.07202	-0.05888	-0.09007	0.06762	0.03608
	0.1744	0.3228	0.0276	0.1135	0.3564	0.6286	0.1926	0.4484	0.5356	0.3428	0.4174	0.6654
	113	142	113	113	113	105	110	113	113	113	146	146
TOTHI	0.23874	0.16721	0.20365	0.24379	0.25665	0.10818	0.16182	0.13402	0.13930	0.21930	0.06188	0.10413
	0.0105	0.0459	0.0298	0.0090	0.0058	0.2697	0.0897	0.1552	0.1394	0.0191	0.4565	0.2094
	114	143	114	114	114	106	111	114	114	114	147	147
TOTCSO	-0.00152	0.08101	-0.06480	-0.04220	-0.01532	0.09046	0.04218	-0.08675	0.00471	0.05048	0.24551	0.92048
	0.9872	0.3361	0.4934	0.6557	0.8715	0.3564	0.6602	0.3587	0.9603	0.5938	0.0027	0.0001
	114	143	114	114	114	106	111	114	114	114	147	147

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCSR	PERFMEAS	INSEN	CLIENTSO	COMMUNIC	PERFOR	PERSEVER	SELFCONT	EAGERNES	IDENTSOL	RPISP	RPCSO
TOTCOMM	0.09276	0.00433	0.07249	0.10271	0.08611	0.03275	0.08881	-0.00674	-0.01097	0.11827	0.36208	0.25832
	0.3263	0.9591	0.4434	0.2768	0.3623	0.7390	0.3540	0.9432	0.9078	0.2101	0.0001	0.0016
	114	143	114	114	114	106	111	114	114	114	147	147
TOTISEN	-0.11068	-0.09020	-0.06069	-0.12347	-0.12437	-0.17122	-0.08907	-0.08114	-0.04720	-0.05980	0.31989	0.28545
	0.2411	0.2840	0.5212	0.1906	0.1874	0.0793	0.3525	0.3908	0.6180	0.5274	0.0001	0.0005
	114	143	114	114	114	106	111	114	114	114	147	147
TOTCOOP	0.08624	-0.08261	0.10825	0.06110	0.09304	-0.00048	0.02637	0.10653	0.11166	0.09756	-0.01755	-0.11868
	0.3638	0.3284	0.2538	0.5203	0.3270	0.9961	0.7845	0.2614	0.2390	0.3039	0.8335	0.1536
	113	142	113	113	113	105	110	113	113	113	146	146
TOTPERF	0.05328	-0.06154	0.01270	0.14152	0.04707	0.09459	0.01010	-0.01772	0.07524	0.06047	0.38413	0.37159
	0.5734	0.4653	0.8933	0.1331	0.6189	0.3348	0.9162	0.8515	0.4263	0.5227	0.0001	0.0001
	114	143	114	114	114	106	111	114	114	114	147	147
TOTPERS	0.12595	0.21711	0.03148	0.18113	0.09651	0.19058	0.21886	-0.04263	0.12946	0.10143	0.00160	0.08113
	0.1818	0.0092	0.7395	0.0538	0.3070	0.0504	0.0210	0.6525	0.1698	0.2829	0.9847	0.3287
	114	143	114	114	114	106	111	114	114	114	147	147
TOTSELF	0.03136	-0.01398	-0.05729	0.02917	0.01618	-0.06482	-0.00834	0.03984	0.03220	0.04133	0.19353	0.43799
	0.7405	0.8684	0.5449	0.7580	0.8643	0.5091	0.9308	0.6738	0.7338	0.6624	0.0188	0.0001
	114	143	114	114	114	106	111	114	114	114	147	147

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	RPCOMM	RPISEN	RPPERF	RPSELF	CSISP	CSHI	CSPERF	CSPERS	CCSQISP	CCSQEL	CCSQHI	CCSQCSO
TOTCSR	0.09602	-0.11508	0.04090	0.04425	0.08166	0.19391	0.15986	0.11506	-0.06320	-0.12866	0.04060	0.07054
	0.3095	0.2228	0.6657	0.6402	0.3877	0.0387	0.0893	0.2228	0.5060	0.1744	0.6694	0.4578
	114	114	114	114	114	114	114	114	113	113	113	113
PERFMEAS	0.00973	-0.09056	0.02949	-0.00168	0.10248	0.18952	0.14958	0.17306	-0.00644	-0.08356	-0.07216	0.13188
	0.9082	0.2821	0.7266	0.9841	0.2233	0.0234	0.0746	0.0387	0.9393	0.3228	0.3934	0.1177
	143	143	143	143	143	143	143	143	142	142	142	142
INSEN	0.07509	-0.05873	0.02082	-0.04770	0.05639	0.13226	0.06233	0.00583	-0.10312	-0.20729	0.01687	0.01023
	0.4272	0.5348	0.8260	0.6143	0.5512	0.1607	0.5100	0.9509	0.2771	0.0276	0.8592	0.9144
	114	114	114	114	114	114	114	114	113	113	113	113
CLIENTSO	0.11785	-0.12987	0.13714	0.03693	0.05450	0.09078	0.18663	0.16343	-0.11934	-0.14972	0.00798	0.07233
	0.2118	0.1685	0.1457	0.6965	0.5646	0.3368	0.0468	0.0823	0.2080	0.1135	0.9332	0.4464
	114	114	114	114	114	114	114	114	113	113	113	113
COMMUNIC	0.09140	-0.13280	0.01004	0.03351	0.05320	0.16470	0.07193	0.05922	-0.00141	-0.08756	0.08396	0.10863
	0.3334	0.1590	0.9155	0.7234	0.5740	0.0799	0.4470	0.5314	0.9882	0.3564	0.3766	0.2521
	114	114	114	114	114	114	114	114	113	113	113	113
PERFOR	0.05093	-0.17454	0.06541	-0.05783	0.23544	0.25435	0.20726	0.19763	-0.05827	-0.04775	0.01088	0.13845
	0.6041	0.0735	0.5053	0.5560	0.0151	0.0085	0.0330	0.0423	0.5549	0.6286	0.9123	0.1590
	106	106	106	106	106	106	106	106	105	105	105	105
PERSEVER	0.08503	-0.09755	0.03203	-0.00535	0.09565	0.25589	0.23247	0.18543	-0.03282	-0.12518	0.05828	0.11197
	0.3749	0.3084	0.7386	0.9556	0.3180	0.0067	0.0141	0.0514	0.7336	0.1926	0.5453	0.2442
	111	111	111	111	111	111	111	111	110	110	110	110
SELFCONT	0.00461	-0.07447	-0.04975	0.06184	-0.02493	0.14706	0.07180	-0.03536	-0.04954	-0.07202	0.03179	0.00000
	0.9612	0.4310	0.5991	0.5134	0.7924	0.1184	0.4478	0.7088	0.6023	0.4484	0.7382	1.0000
	114	114	114	114	114	114	114	114	113	113	113	113
EAGERNES	-0.02692	-0.05287	0.01041	0.03588	0.06563	0.21910	0.15666	0.13644	-0.01076	-0.05888	0.09986	0.07668
	0.7761	0.5764	0.9124	0.7047	0.4878	0.0192	0.0960	0.1478	0.9100	0.5356	0.2926	0.4196
	114	114	114	114	114	114	114	114	113	113	113	113
IDENTSOL	0.11703	-0.06517	0.05642	0.05309	0.03826	0.12467	0.09614	0.08042	-0.01862	-0.09007	0.01627	0.02131
	0.2150	0.4909	0.5510	0.5748	0.6861	0.1863	0.3089	0.3950	0.8448	0.3428	0.8642	0.8228
	114	114	114	114	114	114	114	114	113	113	113	113
RPISP	0.35681	0.33711	0.38950	0.19353	0.10457	-0.01873	0.07889	0.00020	0.07273	0.06762	0.08211	-0.03347
	0.0001	0.0001	0.0001	0.0188	0.2075	0.8219	0.3422	0.9980	0.3830	0.4174	0.3245	0.6883
	147	147	147	147	147	147	147	147	146	146	146	146
RPCSO	0.24113	0.29947	0.46039	0.43799	0.09631	-0.03597	0.10328	0.07407	0.05193	0.03608	0.07635	0.12938
	0.0033	0.0002	0.0001	0.0001	0.2459	0.6653	0.2132	0.3726	0.5336	0.6654	0.3597	0.1196
	147	147	147	147	147	147	147	147	146	146	146	146
RPCOMM	1.00000	0.24075	0.34504	0.34899	0.23003	-0.01537	0.07640	0.09645	-0.14378	-0.06123	0.05541	-0.02533
	0.0	0.0033	0.0001	0.0001	0.0051	0.8534	0.3577	0.2452	0.0834	0.4628	0.5065	0.7615
	147	147	147	147	147	147	147	147	146	146	146	146

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	RPCOMM	RPISEN	RPPERF	RPSELF	CSISP	CSHI	CSPERF	CSPERS	CCSQISP	CCSQEL	CCSQHI	CCSQCSO
RPISEN	0.24075	1.00000	0.12678	0.39362	0.12792	0.04374	0.16841	0.11716	-0.08001	-0.00390	0.11555	0.10324
	0.0033	0.0	0.1260	0.0001	0.1226	0.5988	0.0414	0.1576	0.3371	0.9627	0.1649	0.2150
	147	147	147	147	147	147	147	147	146	146	146	146
RPPERF	0.34504	0.12678	1.00000	0.31454	0.10629	-0.08640	0.11964	0.13310	-0.09828	-0.04345	0.03208	0.01690
	0.0001	0.1260	0.0	0.0001	0.2001	0.2981	0.1489	0.1080	0.2379	0.6025	0.7007	0.8395
	147	147	147	147	147	147	147	147	146	146	146	146
RPSELF	0.34899	0.39362	0.31454	1.00000	-0.05626	-0.08473	0.02174	-0.00418	0.00017	0.06765	0.04036	0.05170
	0.0001	0.0001	0.0001	0.0	0.4985	0.3075	0.7938	0.9600	0.9984	0.4172	0.6286	0.5354
	147	147	147	147	147	147	147	147	146	146	146	146
CSISP	0.23003	0.12792	0.10629	-0.05626	1.00000	0.36368	0.41882	0.48316	-0.08360	0.01346	0.02549	0.19095
	0.0051	0.1226	0.2001	0.4985	0.0	0.0001	0.0001	0.0001	0.3158	0.8719	0.7600	0.0210
	147	147	147	147	147	147	147	147	146	146	146	146
CSHI	-0.01537	0.04374	-0.08640	-0.08473	0.36368	1.00000	0.47827	0.43782	0.07365	0.13174	0.09649	0.19590
	0.8534	0.5988	0.2981	0.3075	0.0001	0.0	0.0001	0.0001	0.3770	0.1130	0.2466	0.0178
	147	147	147	147	147	147	147	147	146	146	146	146
CSPERF	0.07640	0.16841	0.11964	0.02174	0.41882	0.47827	1.00000	0.72270	0.03763	0.13488	0.05472	0.07819
	0.3577	0.0414	0.1489	0.7938	0.0001	0.0001	0.0	0.0001	0.6521	0.1046	0.5118	0.3482
	147	147	147	147	147	147	147	147	146	146	146	146
CSPERS	0.09645	0.11716	0.13310	-0.00418	0.48316	0.43782	0.72270	1.00000	-0.01011	0.08907	0.07452	0.18120
	0.2452	0.1576	0.1080	0.9600	0.0001	0.0001	0.0001	0.0	0.9036	0.2850	0.3714	0.0286
	147	147	147	147	147	147	147	147	146	146	146	146
CCSQISP	-0.14378	-0.08001	-0.09828	0.00017	-0.08360	0.07365	0.03763	-0.01011	1.00000	0.69157	0.43747	0.28062
	0.0834	0.3371	0.2379	0.9984	0.3158	0.3770	0.6521	0.9036	0.0	0.0001	0.0001	0.0006
	146	146	146	146	146	146	146	146	146	146	146	146
CCSQEL	-0.06123	-0.00390	-0.04345	0.06765	0.01346	0.13174	0.13488	0.08907	0.69157	1.00000	0.62667	0.28457
	0.4628	0.9627	0.6025	0.4172	0.8719	0.1130	0.1046	0.2850	0.0001	0.0	0.0001	0.0005
	146	146	146	146	146	146	146	146	146	146	146	146
CCSQHI	0.05541	0.11555	0.03208	0.04036	0.02549	0.09649	0.05472	0.07452	0.43747	0.62667	1.00000	0.37806
	0.5065	0.1649	0.7007	0.6286	0.7600	0.2466	0.5118	0.3714	0.0001	0.0001	0.0	0.0001
	146	146	146	146	146	146	146	146	146	146	146	146
CCSQCSO	-0.02533	0.10324	0.01690	0.05170	0.19095	0.19590	0.07819	0.18120	0.28062	0.28457	0.37806	1.00000
	0.7615	0.2150	0.8395	0.5354	0.0210	0.0178	0.3482	0.0286	0.0006	0.0005	0.0001	0.0
	146	146	146	146	146	146	146	146	146	146	146	146
CCSQCOMM	-0.12032	0.05690	-0.02229	-0.08721	0.01755	0.10088	-0.00776	0.05033	0.36577	0.16657	-0.04600	0.06866
	0.1480	0.4951	0.7894	0.2953	0.8334	0.2257	0.9259	0.5463	0.0001	0.0445	0.5814	0.4102
	146	146	146	146	146	146	146	146	146	146	146	146
CCSQISEN	-0.06066	0.10615	-0.08454	0.01640	0.04534	0.07729	-0.04848	0.01926	0.13831	0.05807	0.04112	0.50965
	0.4671	0.2022	0.3103	0.8443	0.5869	0.3538	0.5612	0.8175	0.0959	0.4863	0.6222	0.0001
	146	146	146	146	146	146	146	146	146	146	146	146

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	RPCOMM	RPISEN	RPPERF	RPSELF	CSISP	CSHI	CSPERF	CSPERS	CCSQISP	CCSQEL	CCSQHI	CCSQCSO
CCSQCOOP	-0.10800	0.04961	-0.14000	-0.03175	0.01834	-0.05331	-0.02127	-0.03427	0.07906	-0.07830	-0.07244	0.19595
	0.1944	0.5521	0.0919	0.7036	0.8261	0.5228	0.7989	0.6814	0.3428	0.3475	0.3849	0.0178
	146	146	146	146	146	146	146	146	146	146	146	146
CCSQPERF	0.00956	0.10043	0.00640	-0.01516	0.12026	0.16751	0.09526	0.16694	0.47834	0.53620	0.77686	0.49042
	0.9088	0.2278	0.9388	0.8559	0.1482	0.0433	0.2527	0.0440	0.0001	0.0001	0.0001	0.0001
	146	146	146	146	146	146	146	146	146	146	146	146
CCSQPERS	-0.02866	-0.05604	0.05375	-0.00886	0.05822	0.13077	0.05457	0.07643	0.61205	0.43280	0.34913	0.23300
	0.7313	0.5017	0.5193	0.9155	0.4852	0.1156	0.5130	0.3592	0.0001	0.0001	0.0001	0.0047
	146	146	146	146	146	146	146	146	146	146	146	146
CCSQSELF	-0.01050	-0.07403	-0.04803	0.06852	-0.01553	0.06334	-0.10476	-0.03275	0.31531	0.19036	0.05158	0.26122
	0.8999	0.3745	0.5648	0.4112	0.8524	0.4476	0.2083	0.6947	0.0001	0.0214	0.5364	0.0014
	146	146	146	146	146	146	146	146	146	146	146	146
VERBISP	0.05223	0.06089	0.09340	-0.06195	-0.01569	0.00898	-0.03568	-0.06204	-0.05170	0.02972	0.02664	-0.06432
	0.5298	0.4638	0.2605	0.4560	0.8504	0.9141	0.6679	0.4554	0.5355	0.7218	0.7496	0.4405
	147	147	147	147	147	147	147	147	146	146	146	146
VERBHI	0.01947	0.03170	-0.03881	0.12148	-0.03255	-0.00802	-0.13694	-0.06578	0.11485	0.15985	0.09902	-0.06801
	0.8162	0.7050	0.6430	0.1455	0.6975	0.9238	0.1005	0.4318	0.1705	0.0556	0.2377	0.4180
	145	145	145	145	145	145	145	145	144	144	144	144
CHECKHI	0.16087	0.01820	0.01584	0.02663	0.22955	0.08570	0.15537	0.11747	-0.00800	-0.06887	0.04894	0.12793
	0.0516	0.8268	0.8490	0.7489	0.0052	0.3020	0.0602	0.1565	0.9237	0.4088	0.5574	0.1238
	147	147	147	147	147	147	147	147	146	146	146	146
CLASSHI	0.14360	0.03632	0.16704	-0.00500	0.10232	-0.00733	0.07061	0.11730	-0.11531	-0.14745	0.00962	0.13862
	0.0827	0.6623	0.0432	0.9520	0.2175	0.9298	0.3954	0.1571	0.1658	0.0757	0.9083	0.0952
	147	147	147	147	147	147	147	147	146	146	146	146
NUMISP	0.09244	0.01093	-0.05321	0.04022	0.13346	0.15943	0.01364	-0.07091	0.03769	0.17481	0.04442	0.07758
	0.2654	0.8955	0.5221	0.6286	0.1071	0.0538	0.8697	0.3934	0.6515	0.0348	0.5944	0.3520
	147	147	147	147	147	147	147	147	146	146	146	146
TOTISP	0.26860	0.28641	0.36603	0.12673	0.11717	-0.02589	0.11458	0.02240	0.04310	0.03453	0.02707	-0.03000
	0.0010	0.0004	0.0001	0.1261	0.1576	0.7556	0.1670	0.7877	0.6055	0.6791	0.7456	0.7193
	147	147	147	147	147	147	147	147	146	146	146	146
TOTEL	-0.06123	-0.00390	-0.04345	0.06765	0.01346	0.13174	0.13488	0.08907	0.69157	1.00000	0.62667	0.28457
	0.4628	0.9627	0.6025	0.4172	0.8719	0.1130	0.1046	0.2850	0.0001	0.0001	0.0001	0.0005
	146	146	146	146	146	146	146	146	146	146	146	146
TOTHI	0.19084	0.06114	0.12930	0.01247	0.11145	0.06281	0.09330	0.13956	-0.08339	-0.11086	0.02419	0.07217
	0.0206	0.4620	0.1186	0.8809	0.1790	0.4498	0.2610	0.0918	0.3170	0.1828	0.7720	0.3866
	147	147	147	147	147	147	147	147	146	146	146	146
TOTCSO	0.23673	0.21462	0.41065	0.38152	0.14394	-0.09470	0.08984	0.07551	-0.00405	-0.01813	0.02915	0.18875
	0.0039	0.0090	0.0001	0.0001	0.0820	0.2539	0.2792	0.3633	0.9613	0.8280	0.7269	0.0225
	147	147	147	147	147	147	147	147	146	146	146	146

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	RPCOMM	RPISEN	RPPERF	RPSELF	CSISP	CSHI	CSPERF	CSPERS	CCSQISP	CCSQEL	CCSQHI	CCSQCSO
TOTCOMM	0.99112	0.23908	0.35158	0.34719	0.21852	-0.00756	0.08232	0.08988	-0.13710	-0.05610	0.04525	-0.03908
	0.0001	0.0035	0.0001	0.0001	0.0078	0.9276	0.3216	0.2790	0.0989	0.5013	0.5876	0.6395
	147	147	147	147	147	147	147	147	146	146	146	146
TOTISEN	0.22231	0.99053	0.10805	0.38114	0.14239	0.05431	0.16393	0.12540	-0.05187	0.02046	0.14278	0.13285
	0.0068	0.0001	0.1927	0.0001	0.0854	0.5135	0.0473	0.1302	0.5341	0.8064	0.0856	0.1099
	147	147	147	147	147	147	147	147	146	146	146	146
TOTCOOP	-0.10874	0.03745	-0.14269	-0.04317	0.02895	-0.04516	-0.02550	-0.02825	0.08207	-0.07082	-0.07587	0.20620
	0.1914	0.6536	0.0858	0.6049	0.7287	0.5884	0.7599	0.7350	0.3247	0.3956	0.3627	0.0125
	146	146	146	146	146	146	146	146	146	146	146	146
TOTPERF	0.28932	0.21130	0.83523	0.22634	0.20564	-0.05213	0.19643	0.14439	-0.05401	0.01906	0.07246	0.09281
	0.0004	0.0102	0.0001	0.0058	0.0125	0.5306	0.0171	0.0810	0.5173	0.8194	0.3848	0.2652
	147	147	147	147	147	147	147	147	146	146	146	146
TOTPERS	0.13580	0.15987	0.12790	0.03604	0.49828	0.36556	0.70145	0.93394	-0.02501	0.05647	0.03314	0.22392
	0.1010	0.0531	0.1226	0.6647	0.0001	0.0001	0.0001	0.0001	0.7644	0.4984	0.6913	0.0066
	147	147	147	147	147	147	147	147	146	146	146	146
TOTSELF	0.34899	0.39362	0.29885	0.98026	-0.03836	-0.04727	0.05324	0.01337	-0.01221	0.06765	0.04036	0.03648
	0.0001	0.0001	0.0002	0.0001	0.6446	0.5697	0.5219	0.8724	0.8837	0.4172	0.6286	0.6620
	147	147	147	147	147	147	147	147	146	146	146	146

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CCSQCOMM	CCSQISEN	CCSQCOOP	CCSQPERF	CCSQPERS	CCSQSELF	VERBISP	VERBHI	CHECKHI	CLASSHI	NUMISP	TOTISP
TOTCSR	-0.02230	0.03701	0.08624	0.01433	0.07023	0.04889	-0.07017	-0.14663	0.15750	0.21637	0.11919	0.05168
	0.8146	0.6971	0.3638	0.8803	0.4598	0.6071	0.4581	0.1212	0.0942	0.0208	0.2066	0.5850
	113	113	113	113	113	113	114	113	114	114	114	114
PERFMEAS	-0.09606	-0.02261	-0.09664	0.00731	0.12279	0.06305	-0.04273	-0.32240	0.19055	0.22378	0.06922	-0.13249
	0.2554	0.7894	0.2526	0.9312	0.1455	0.4560	0.6123	0.0001	0.0226	0.0072	0.4114	0.1147
	142	142	142	142	142	142	143	141	143	143	143	143
INSEN	0.04716	0.09649	0.10825	0.01646	0.05596	0.00940	-0.09089	-0.15142	0.07785	0.10136	0.07214	0.12554
	0.6199	0.3093	0.2538	0.8626	0.5560	0.9213	0.3362	0.1094	0.4103	0.2833	0.4456	0.1832
	113	113	113	113	113	113	114	113	114	114	114	114
CLIENTSO	-0.02504	0.08950	0.06110	-0.00636	0.05443	0.02631	-0.10130	-0.19011	0.10076	0.19696	0.09296	0.03893
	0.7923	0.3459	0.5203	0.9467	0.5669	0.7821	0.2835	0.0437	0.2861	0.0357	0.3253	0.6809
	113	113	113	113	113	113	114	113	114	114	114	114
COMMUNIC	0.03130	0.12163	0.09304	0.09657	0.11679	0.09355	0.00821	-0.06371	0.18451	0.26668	0.12609	0.01031
	0.7420	0.1994	0.3270	0.3089	0.2180	0.3244	0.9309	0.5026	0.0494	0.0041	0.1813	0.9133
	113	113	113	113	113	113	114	113	114	114	114	114
PERFOR	-0.11817	-0.07420	-0.00048	0.06483	0.08153	0.03812	0.00066	-0.15033	0.13784	0.12827	0.17017	-0.11186
	0.2299	0.4519	0.9961	0.5111	0.4083	0.6995	0.9946	0.1258	0.1588	0.1901	0.0812	0.2536
	105	105	105	105	105	105	106	105	106	106	106	106
PERSEVER	0.01952	0.03759	0.02637	0.07963	0.12835	0.04036	-0.13399	-0.12194	0.12595	0.14567	0.05857	-0.09322
	0.8396	0.6966	0.7845	0.4083	0.1814	0.6754	0.1609	0.2044	0.1878	0.1271	0.5415	0.3305
	110	110	110	110	110	110	111	110	111	111	111	111
SELFCONT	-0.04626	0.06125	0.10653	-0.01365	0.05794	0.03317	-0.08934	-0.05383	0.16398	0.13088	0.16085	0.04930
	0.6266	0.5193	0.2614	0.8859	0.5421	0.7273	0.3445	0.5712	0.0813	0.1652	0.0873	0.6024
	113	113	113	113	113	113	114	113	114	114	114	114
EAGERNES	-0.04483	-0.09337	0.11166	0.00563	0.04701	-0.02344	-0.10493	-0.15570	0.05686	0.16601	0.06643	0.07228
	0.6373	0.3253	0.2390	0.9528	0.6210	0.8054	0.2666	0.0996	0.5479	0.0775	0.4825	0.4448
	113	113	113	113	113	113	114	113	114	114	114	114
IDENTSOL	0.05338	0.04750	0.09756	-0.02753	0.07877	0.08170	-0.03793	-0.11840	0.10452	0.20043	0.05676	0.13528
	0.5744	0.6173	0.3039	0.7722	0.4069	0.3896	0.6887	0.2116	0.2684	0.0325	0.5486	0.1513
	113	113	113	113	113	113	114	113	114	114	114	114
RPISP	0.12460	-0.04740	-0.01556	0.06366	0.04434	0.01818	0.04397	-0.01901	0.05786	0.02248	0.01019	0.88103
	0.1340	0.5700	0.8521	0.4453	0.5951	0.8275	0.5969	0.8205	0.4864	0.7870	0.9025	0.0001
	146	146	146	146	146	146	147	145	147	147	147	147
RPCSO	-0.05047	-0.02858	-0.10674	0.08934	0.06623	0.02316	0.01824	-0.00886	0.13744	0.08148	-0.09236	0.31170
	0.5452	0.7320	0.1997	0.2835	0.4270	0.7814	0.8265	0.9158	0.0969	0.3266	0.2659	0.0001
	146	146	146	146	146	146	147	145	147	147	147	147
RPCOMM	-0.12032	-0.06066	-0.10800	0.00956	-0.02866	-0.01050	0.05223	0.01947	0.16087	0.14360	0.09244	0.26860
	0.1480	0.4671	0.1944	0.9088	0.7313	0.8999	0.5298	0.8162	0.0516	0.0827	0.2654	0.0010
	146	146	146	146	146	146	147	145	147	147	147	147

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CCSQCOMM	CCSQISEN	CCSQCOOP	CCSQPERF	CCSQPERS	CCSQSELF	VERBISP	VERBHI	CHECKHI	CLASSHI	NUMISP	TOTISP
RPISEN	0.05690	0.10615	0.04961	0.10043	-0.05604	-0.07403	0.06089	0.03170	0.01820	0.03632	0.01093	0.28641
	0.4951	0.2022	0.5521	0.2278	0.5017	0.3745	0.4638	0.7050	0.8268	0.6623	0.8955	0.0004
	146	146	146	146	146	146	147	145	147	147	147	147
RPPERF	-0.02229	-0.08454	-0.14000	0.00640	0.05375	-0.04803	0.09340	-0.03881	0.01584	0.16704	-0.05321	0.36603
	0.7894	0.3103	0.0919	0.9388	0.5193	0.5648	0.2605	0.6430	0.8490	0.0432	0.5221	0.0001
	146	146	146	146	146	146	147	145	147	147	147	147
RPSELF	-0.08721	0.01640	-0.03175	-0.01516	-0.00886	0.06852	-0.06195	0.12148	0.02663	-0.00500	0.04022	0.12673
	0.2953	0.8443	0.7036	0.8559	0.9155	0.4112	0.4560	0.1455	0.7489	0.9520	0.6286	0.1261
	146	146	146	146	146	146	147	145	147	147	147	147
CSISP	0.01755	0.04534	0.01834	0.12026	0.05822	-0.01553	-0.01569	-0.03255	0.22955	0.10232	0.13346	0.11717
	0.8334	0.5869	0.8261	0.1482	0.4852	0.8524	0.8504	0.6975	0.0052	0.2175	0.1071	0.1576
	146	146	146	146	146	146	147	145	147	147	147	147
CSHI	0.10088	0.07729	-0.05331	0.16751	0.13077	0.06334	0.00898	-0.00802	0.08570	-0.00733	0.15943	-0.02589
	0.2257	0.3538	0.5228	0.0433	0.1156	0.4476	0.9141	0.9238	0.3020	0.9298	0.0538	0.7556
	146	146	146	146	146	146	147	145	147	147	147	147
CSPERF	-0.00776	-0.04848	-0.02127	0.09526	0.05457	-0.10476	-0.03568	-0.13694	0.15537	0.07061	0.01364	0.11458
	0.9259	0.5612	0.7989	0.2527	0.5130	0.2083	0.6679	0.1005	0.0602	0.3954	0.8697	0.1670
	146	146	146	146	146	146	147	145	147	147	147	147
CSPERS	0.05033	0.01926	-0.03427	0.16694	0.07643	-0.03275	-0.06204	-0.06578	0.11747	0.11730	-0.07091	0.02240
	0.5463	0.8175	0.6814	0.0440	0.3592	0.6947	0.4554	0.4318	0.1565	0.1571	0.3934	0.7877
	146	146	146	146	146	146	147	145	147	147	147	147
CCSQISP	0.36577	0.13831	0.07906	0.47834	0.61205	0.31531	-0.05170	0.11485	-0.00800	-0.11531	0.03769	0.04310
	0.0001	0.0959	0.3428	0.0001	0.0001	0.0001	0.5355	0.1705	0.9237	0.1658	0.6515	0.6055
	146	146	146	146	146	146	146	144	146	146	146	146
CCSQEL	0.16657	0.05807	-0.07830	0.53620	0.43280	0.19036	0.02972	0.15985	-0.06887	-0.14745	0.17481	0.03453
	0.0445	0.4863	0.3475	0.0001	0.0001	0.0214	0.7218	0.0556	0.4088	0.0757	0.0348	0.6791
	146	146	146	146	146	146	146	144	146	146	146	146
CCSQHI	-0.04600	0.04112	-0.07244	0.77686	0.34913	0.05158	0.02664	0.09902	0.04894	0.00962	0.04442	0.02707
	0.5814	0.6222	0.3849	0.0001	0.0001	0.5364	0.7496	0.2377	0.5574	0.9083	0.5944	0.7456
	146	146	146	146	146	146	146	144	146	146	146	146
CCSQCSO	0.06866	0.50965	0.19595	0.49042	0.23300	0.26122	-0.06432	-0.06801	0.12793	0.13862	0.07758	-0.03000
	0.4102	0.0001	0.0178	0.0001	0.0047	0.0014	0.4405	0.4180	0.1238	0.0952	0.3520	0.7193
	146	146	146	146	146	146	146	144	146	146	146	146
CCSQCOMM	1.00000	0.46537	0.46293	0.06946	0.27243	0.24509	-0.00898	0.16771	-0.07333	-0.12447	-0.07627	0.17035
	0.0	0.0001	0.0001	0.4048	0.0009	0.0029	0.9143	0.0445	0.3791	0.1344	0.3602	0.0398
	146	146	146	146	146	146	146	144	146	146	146	146
CCSQISEN	0.46537	1.00000	0.53711	0.18722	-0.00902	0.25660	-0.05261	0.01721	0.00531	0.06439	0.09618	-0.04039
	0.0001	0.0	0.0001	0.0236	0.9139	0.0018	0.5283	0.8378	0.9493	0.4401	0.2481	0.6283
	146	146	146	146	146	146	146	144	146	146	146	146

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CCSQCOMM	CCSQISEN	CCSQCOOP	CCSQPERF	CCSQPERS	CCSQSELF	VERBISP	VERBHI	CHECKHI	CLASSHI	NUMISP	TOTISP
CCSQCOOP	0.46293	0.53711	1.00000	-0.02438	-0.01619	0.15196	-0.02278	-0.00669	-0.03223	-0.03759	-0.03741	0.02986
	0.0001	0.0001	0.0	0.7702	0.8462	0.0671	0.7850	0.9366	0.6994	0.6524	0.6539	0.7205
	146	146	146	146	146	146	146	144	146	146	146	146
CCSQPERF	0.06946	0.18722	-0.02438	1.00000	0.52671	0.26692	-0.03397	0.08589	-0.03555	-0.02785	0.03103	0.01033
	0.4048	0.0236	0.7702	0.0	0.0001	0.0011	0.6840	0.3060	0.6701	0.7387	0.7101	0.9015
	146	146	146	146	146	146	146	144	146	146	146	146
CCSQPERS	0.27243	-0.00902	-0.01619	0.52671	1.00000	0.42814	-0.14167	0.10088	-0.04967	-0.03825	-0.07591	0.01622
	0.0009	0.9139	0.8462	0.0001	0.0	0.0001	0.0881	0.2289	0.5516	0.6467	0.3625	0.8459
	146	146	146	146	146	146	146	144	146	146	146	146
CCSQSELF	0.24509	0.25660	0.15196	0.26692	0.42814	1.00000	-0.08964	0.03050	-0.00389	0.03663	0.08031	0.01702
	0.0029	0.0018	0.0671	0.0011	0.0001	0.0	0.2819	0.7167	0.9628	0.6607	0.3353	0.8384
	146	146	146	146	146	146	146	144	146	146	146	146
VERBISP	-0.00898	-0.05261	-0.02278	-0.03397	-0.14167	-0.08964	1.00000	0.35592	0.20330	0.31689	0.41587	0.08250
	0.9143	0.5283	0.7850	0.6840	0.0881	0.2819	0.0	0.0001	0.0135	0.0001	0.0001	0.3205
	146	146	146	146	146	146	147	145	147	147	147	147
VERBHI	0.16771	0.01721	-0.00669	0.08589	0.10088	0.03050	0.35592	1.00000	0.07808	-0.02528	0.07515	-0.01073
	0.0445	0.8378	0.9366	0.3060	0.2289	0.7167	0.0001	0.0	0.3506	0.7628	0.3690	0.8981
	144	144	144	144	144	144	145	145	145	145	145	145
CHECKHI	-0.07333	0.00531	-0.03223	-0.03555	-0.04967	-0.00389	0.20330	0.07808	1.00000	0.45331	0.24682	0.01299
	0.3791	0.9493	0.6994	0.6701	0.5516	0.9628	0.0135	0.3506	0.0	0.0001	0.0026	0.8759
	146	146	146	146	146	146	147	145	147	147	147	147
CLASSHI	-0.12447	0.06439	-0.03759	-0.02785	-0.03825	0.03663	0.31689	-0.02528	0.45331	1.00000	0.21651	-0.01876
	0.1344	0.4401	0.6524	0.7387	0.6467	0.6607	0.0001	0.7628	0.0001	0.0	0.0084	0.8216
	146	146	146	146	146	146	147	145	147	147	147	147
NUMISP	-0.07627	0.09618	-0.03741	0.03103	-0.07591	0.08031	0.41587	0.07515	0.24682	0.21651	1.00000	-0.01133
	0.3602	0.2481	0.6539	0.7101	0.3625	0.3353	0.0001	0.3690	0.0026	0.0084	0.0	0.8917
	146	146	146	146	146	146	147	145	147	147	147	147
TOTISP	0.17035	-0.04039	0.02986	0.01033	0.01622	0.01702	0.08250	-0.01073	0.01299	-0.01876	-0.01133	1.00000
	0.0398	0.6283	0.7205	0.9015	0.8459	0.8384	0.3205	0.8981	0.8759	0.8216	0.8917	0.0
	146	146	146	146	146	146	147	145	147	147	147	147
TOTEL	0.16657	0.05807	-0.07830	0.53620	0.43280	0.19036	0.02972	0.15985	-0.06887	-0.14745	0.17481	0.03453
	0.0445	0.4863	0.3475	0.0001	0.0001	0.0214	0.7218	0.0556	0.4088	0.0757	0.0348	0.6791
	146	146	146	146	146	146	146	144	146	146	146	146
TOTHI	-0.08448	0.07231	-0.09759	-0.01925	-0.03867	0.08085	0.32881	0.07947	0.59338	0.80854	0.22084	0.07816
	0.3107	0.3858	0.2413	0.8176	0.6431	0.3320	0.0001	0.3421	0.0001	0.0001	0.0072	0.3467
	146	146	146	146	146	146	147	145	147	147	147	147
TOTCSO	-0.07209	0.05124	-0.04329	0.05401	0.01782	0.01147	0.00830	0.00869	0.20071	0.14077	-0.04668	0.21762
	0.3872	0.5391	0.6039	0.5173	0.8310	0.8907	0.9205	0.9174	0.0148	0.0890	0.5745	0.0081
	146	146	146	146	146	146	147	145	147	147	147	147

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CCSQCOMM	CCSQISEN	CCSQCOOP	CCSQPERF	CCSQPERS	CCSQSELF	VERBISP	VERBHI	CHECKHI	CLASSHI	NUMISP	TOTISP
TOTCOMM	-0.11845	-0.07158	-0.12008	0.00203	-0.01658	-0.01316	0.05410	0.03700	0.14789	0.14697	0.07395	0.27266
	0.1544	0.3906	0.1488	0.9806	0.8425	0.8747	0.5151	0.6586	0.0738	0.0757	0.3734	0.0008
	146	146	146	146	146	146	147	145	147	147	147	147
TOTISEN	0.06604	0.11757	0.06151	0.13941	-0.02791	-0.04503	0.06464	0.03546	0.01607	0.04211	0.03079	0.26833
	0.4284	0.1576	0.4608	0.0933	0.7381	0.5894	0.4366	0.6720	0.8468	0.6125	0.7112	0.0010
	146	146	146	146	146	146	147	145	147	147	147	147
TOTCOOP	0.46831	0.54380	0.99422	-0.03008	-0.00467	0.16396	-0.03829	-0.02085	-0.02789	-0.05006	-0.03934	0.02816
	0.0001	0.0001	0.0001	0.7186	0.9553	0.0480	0.6463	0.8041	0.7383	0.5485	0.6374	0.7358
	146	146	146	146	146	146	146	144	146	146	146	146
TOTPERF	0.01930	-0.00793	-0.06186	0.04104	0.06822	-0.00360	0.18345	0.02308	0.00827	0.19237	-0.00173	0.37838
	0.8172	0.9243	0.4582	0.6228	0.4133	0.9656	0.0261	0.7829	0.9208	0.0196	0.9834	0.0001
	146	146	146	146	146	146	147	145	147	147	147	147
TOTPERS	0.03621	0.08602	0.00064	0.18270	0.10497	0.04616	-0.09915	-0.10778	0.13075	0.14032	-0.09469	0.00330
	0.6644	0.3019	0.9939	0.0273	0.2073	0.5801	0.2322	0.1969	0.1145	0.0900	0.2539	0.9683
	146	146	146	146	146	146	147	145	147	147	147	147
TOTSELF	-0.11087	0.00105	-0.03175	-0.03064	-0.02276	0.06852	-0.05697	0.08570	0.01145	-0.00851	0.03861	0.12673
	0.1828	0.9900	0.7036	0.7135	0.7851	0.4112	0.4931	0.3054	0.8905	0.9185	0.6425	0.1261
	146	146	146	146	146	146	147	145	147	147	147	147

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTEL	TOTHI	TOTCSO	TOTCOMM	TOTISEN	TOTCOOP	TOTPERF	TOTPERS	TOTSELF
TOTCSR	-0.12866	0.23874	-0.00152	0.09276	-0.11068	0.08624	0.05328	0.12595	0.03136
	0.1744	0.0105	0.9872	0.3263	0.2411	0.3638	0.5734	0.1818	0.7405
	113	114	114	114	114	113	114	114	114
PERFMEAS	-0.08356	0.16721	0.08101	0.00433	-0.09020	-0.08261	-0.06154	0.21711	-0.01398
	0.3228	0.0459	0.3361	0.9591	0.2840	0.3284	0.4653	0.0092	0.8684
	142	143	143	143	143	142	143	143	143
INSEN	-0.20729	0.20365	-0.06480	0.07249	-0.06069	0.10825	0.01270	0.03148	-0.05729
	0.0276	0.0298	0.4934	0.4434	0.5212	0.2538	0.8933	0.7395	0.5449
	113	114	114	114	114	113	114	114	114
CLIENTSO	-0.14972	0.24379	-0.04220	0.10271	-0.12347	0.06110	0.14152	0.18113	0.02917
	0.1135	0.0090	0.6557	0.2768	0.1906	0.5203	0.1331	0.0538	0.7580
	113	114	114	114	114	113	114	114	114
COMMUNIC	-0.08756	0.25665	-0.01532	0.08611	-0.12437	0.09304	0.04707	0.09651	0.01618
	0.3564	0.0058	0.8715	0.3623	0.1874	0.3270	0.6189	0.3070	0.8643
	113	114	114	114	114	113	114	114	114
PERFOR	-0.04775	0.10818	0.09046	0.03275	-0.17122	-0.00048	0.09459	0.19058	-0.06482
	0.6286	0.2697	0.3564	0.7390	0.0793	0.9961	0.3348	0.0504	0.5091
	105	106	106	106	106	105	106	106	106
PERSEVER	-0.12518	0.16182	0.04218	0.08881	-0.08907	0.02637	0.01010	0.21886	-0.00834
	0.1926	0.0897	0.6602	0.3540	0.3525	0.7845	0.9162	0.0210	0.9308
	110	111	111	111	111	110	111	111	111
SELFCONT	-0.07202	0.13402	-0.08675	-0.00674	-0.08114	0.10653	-0.01772	-0.04263	0.03984
	0.4484	0.1552	0.3587	0.9432	0.3908	0.2614	0.8515	0.6525	0.6738
	113	114	114	114	114	113	114	114	114
EAGERNES	-0.05888	0.13930	0.00471	-0.01097	-0.04720	0.11166	0.07524	0.12946	0.03220
	0.5356	0.1394	0.9603	0.9078	0.6180	0.2390	0.4263	0.1698	0.7338
	113	114	114	114	114	113	114	114	114
IDENTSOL	-0.09007	0.21930	0.05048	0.11827	-0.05980	0.09756	0.06047	0.10143	0.04133
	0.3428	0.0191	0.5938	0.2101	0.5274	0.3039	0.5227	0.2829	0.6624
	113	114	114	114	114	113	114	114	114
RPISP	0.06762	0.06188	0.24551	0.36208	0.31989	-0.01755	0.38413	0.00160	0.19353
	0.4174	0.4565	0.0027	0.0001	0.0001	0.8335	0.0001	0.9847	0.0188
	146	147	147	147	147	146	147	147	147
RPCSO	0.03608	0.10413	0.92048	0.25832	0.28545	-0.11868	0.37159	0.08113	0.43799
	0.6654	0.2094	0.0001	0.0016	0.0005	0.1536	0.0001	0.3287	0.0001
	146	147	147	147	147	146	147	147	147
RPCOMM	-0.06123	0.19084	0.23673	0.99112	0.22231	-0.10874	0.28932	0.13580	0.34899
	0.4628	0.0206	0.0039	0.0001	0.0068	0.1914	0.0004	0.1010	0.0001
	146	147	147	147	147	146	147	147	147

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTEL	TOTHI	TOTCSO	TOTCOMM	TOTISEN	TOTCOOP	TOTPERF	TOTPERS	TOTSELF
RPISEN	-0.00390	0.06114	0.21462	0.23908	0.99053	0.03745	0.21130	0.15987	0.39362
	0.9627	0.4620	0.0090	0.0035	0.0001	0.6536	0.0102	0.0531	0.0001
	146	147	147	147	147	146	147	147	147
RPPERF	-0.04345	0.12930	0.41065	0.35158	0.10805	-0.14269	0.83523	0.12790	0.29885
	0.6025	0.1186	0.0001	0.0001	0.1927	0.0858	0.0001	0.1226	0.0002
	146	147	147	147	147	146	147	147	147
RPSELF	0.06765	0.01247	0.38152	0.34719	0.38114	-0.04317	0.22634	0.03604	0.98026
	0.4172	0.8809	0.0001	0.0001	0.0001	0.6049	0.0058	0.6647	0.0001
	146	147	147	147	147	146	147	147	147
CSISP	0.01346	0.11145	0.14394	0.21852	0.14239	0.02895	0.20564	0.49828	-0.03836
	0.8719	0.1790	0.0820	0.0078	0.0854	0.7287	0.0125	0.0001	0.6446
	146	147	147	147	147	146	147	147	147
CSHI	0.13174	0.06281	-0.09470	-0.00756	0.05431	-0.04516	-0.05213	0.36556	-0.04727
	0.1130	0.4498	0.2539	0.9276	0.5135	0.5884	0.5306	0.0001	0.5697
	146	147	147	147	147	146	147	147	147
CSPERF	0.13488	0.09330	0.08984	0.08232	0.16393	-0.02550	0.19643	0.70145	0.05324
	0.1046	0.2610	0.2792	0.3216	0.0473	0.7599	0.0171	0.0001	0.5219
	146	147	147	147	147	146	147	147	147
CSPERS	0.08907	0.13956	0.07551	0.08988	0.12540	-0.02825	0.14439	0.93394	0.01337
	0.2850	0.0918	0.3633	0.2790	0.1302	0.7350	0.0810	0.0001	0.8724
	146	147	147	147	147	146	147	147	147
CCSQISP	0.69157	-0.08339	-0.00405	-0.13710	-0.05187	0.08207	-0.05401	-0.02501	-0.01221
	0.0001	0.3170	0.9613	0.0989	0.5341	0.3247	0.5173	0.7644	0.8837
	146	146	146	146	146	146	146	146	146
CCSQEL	1.00000	-0.11086	-0.01813	-0.05610	0.02046	-0.07082	0.01906	0.05647	0.06765
	0.0001	0.1828	0.8280	0.5013	0.8064	0.3956	0.8194	0.4984	0.4172
	146	146	146	146	146	146	146	146	146
CCSQHI	0.62667	0.02419	0.02915	0.04525	0.14278	-0.07587	0.07246	0.03314	0.04036
	0.0001	0.7720	0.7269	0.5876	0.0856	0.3627	0.3848	0.6913	0.6286
	146	146	146	146	146	146	146	146	146
CCSQCSO	0.28457	0.07217	0.18875	-0.03908	0.13285	0.20620	0.09281	0.22392	0.03648
	0.0005	0.3866	0.0225	0.6395	0.1099	0.0125	0.2652	0.0066	0.6620
	146	146	146	146	146	146	146	146	146
CCSQCOMM	0.16657	-0.08448	-0.07209	-0.11845	0.06604	0.46831	0.01930	0.03621	-0.11087
	0.0445	0.3107	0.3872	0.1544	0.4284	0.0001	0.8172	0.6644	0.1828
	146	146	146	146	146	146	146	146	146
CCSQISEN	0.05807	0.07231	0.05124	-0.07158	0.11757	0.54380	-0.00793	0.08602	0.00105
	0.4863	0.3858	0.5391	0.3906	0.1576	0.0001	0.9243	0.3019	0.9900
	146	146	146	146	146	146	146	146	146

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTEL	TOTHI	TOTCSO	TOTCOMM	TOTISEN	TOTCOOP	TOTPERF	TOTPERS	TOTSELF
CCSQCOOP	-0.07830	-0.09759	-0.04329	-0.12008	0.06151	0.99422	-0.06186	0.00064	-0.03175
	0.3475	0.2413	0.6039	0.1488	0.4608	0.0001	0.4582	0.9939	0.7036
	146	146	146	146	146	146	146	146	146
CCSQPERF	0.53620	-0.01925	0.05401	0.00203	0.13941	-0.03008	0.04104	0.18270	-0.03064
	0.0001	0.8176	0.5173	0.9806	0.0933	0.7186	0.6228	0.0273	0.7135
	146	146	146	146	146	146	146	146	146
CCSQPERS	0.43280	-0.03867	0.01782	-0.01658	-0.02791	-0.00467	0.06822	0.10497	-0.02276
	0.0001	0.6431	0.8310	0.8425	0.7381	0.9553	0.4133	0.2073	0.7851
	146	146	146	146	146	146	146	146	146
CCSQSELF	0.19036	0.08085	0.01147	-0.01316	-0.04503	0.16396	-0.00360	0.04616	0.06852
	0.0214	0.3320	0.8907	0.8747	0.5894	0.0480	0.9656	0.5801	0.4112
	146	146	146	146	146	146	146	146	146
VERBISP	0.02972	0.32881	0.00830	0.05410	0.06464	-0.03829	0.18345	-0.09915	-0.05697
	0.7218	0.0001	0.9205	0.5151	0.4366	0.6463	0.0261	0.2322	0.4931
	146	147	147	147	147	146	147	147	147
VERBHI	0.15985	0.07947	0.00869	0.03700	0.03546	-0.02085	0.02308	-0.10778	0.08570
	0.0556	0.3421	0.9174	0.6586	0.6720	0.8041	0.7829	0.1969	0.3054
	144	145	145	145	145	144	145	145	145
CHECKHI	-0.06887	0.59338	0.20071	0.14789	0.01607	-0.02789	0.00827	0.13075	0.01145
	0.4088	0.0001	0.0148	0.0738	0.8468	0.7383	0.9208	0.1145	0.8905
	146	147	147	147	147	146	147	147	147
CLASSHI	-0.14745	0.80854	0.14077	0.14697	0.04211	-0.05006	0.19237	0.14032	-0.00851
	0.0757	0.0001	0.0890	0.0757	0.6125	0.5485	0.0196	0.0900	0.9185
	146	147	147	147	147	146	147	147	147
NUMISP	0.17481	0.22084	-0.04668	0.07395	0.03079	-0.03934	-0.00173	-0.09469	0.03861
	0.0348	0.0072	0.5745	0.3734	0.7112	0.6374	0.9834	0.2539	0.6425
	146	147	147	147	147	146	147	147	147
TOTISP	0.03453	0.07816	0.21762	0.27266	0.26833	0.02816	0.37838	0.00330	0.12673
	0.6791	0.3467	0.0081	0.0008	0.0010	0.7358	0.0001	0.9683	0.1261
	146	147	147	147	147	146	147	147	147
TOTEL	1.00000	-0.11086	-0.01813	-0.05610	0.02046	-0.07082	0.01906	0.05647	0.06765
	0.0	0.1828	0.8280	0.5013	0.8064	0.3956	0.8194	0.4984	0.4172
	146	146	146	146	146	146	146	146	146
TOTHI	-0.11086	1.00000	0.12315	0.18748	0.05213	-0.10464	0.13694	0.14408	-0.00208
	0.1828	0.0	0.1373	0.0230	0.5306	0.2088	0.0982	0.0817	0.9801
	146	147	147	147	147	146	147	147	147
TOTCSO	-0.01813	0.12315	1.00000	0.25275	0.20127	-0.05451	0.34613	0.11316	0.38152
	0.8280	0.1373	0.0	0.0020	0.0145	0.5134	0.0001	0.1724	0.0001
	146	147	147	147	147	146	147	147	147

Table A.2
Correlation matrix: Csr

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTEL	TOTHI	TOTCSO	TOTCOMM	TOTISEN	TOTCOOP	TOTPERF	TOTPERS	TOTSELF
TOTCOMM	-0.05610	0.18748	0.25275	1.00000	0.22061	-0.12070	0.29826	0.12889	0.34719
	0.5013	0.0230	0.0020	0.0	0.0073	0.1467	0.0002	0.1197	0.0001
	146	147	147	147	147	146	147	147	147
TOTISEN	0.02046	0.05213	0.20127	0.22061	1.00000	0.04914	0.20565	0.16903	0.38114
	0.8064	0.5306	0.0145	0.0073	0.0	0.5559	0.0125	0.0407	0.0001
	146	147	147	147	147	146	147	147	147
TOTCOOP	-0.07082	-0.10464	-0.05451	-0.12070	0.04914	1.00000	-0.06709	0.00706	-0.04317
	0.3956	0.2088	0.5134	0.1467	0.5559	0.0	0.4211	0.9326	0.6049
	146	146	146	146	146	146	146	146	146
TOTPERF	0.01906	0.13694	0.34613	0.29826	0.20565	-0.06709	1.00000	0.16772	0.22634
	0.8194	0.0982	0.0001	0.0002	0.0125	0.4211	0.0	0.0423	0.0058
	146	147	147	147	147	146	147	147	147
TOTPERS	0.05647	0.14408	0.11316	0.12889	0.16903	0.00706	0.16772	1.00000	0.05324
	0.4984	0.0817	0.1724	0.1197	0.0407	0.9326	0.0423	0.0	0.5219
	146	147	147	147	147	146	147	147	147
TOTSELF	0.06765	-0.00208	0.38152	0.34719	0.38114	-0.04317	0.22634	0.05324	1.00000
	0.4172	0.9801	0.0001	0.0001	0.0001	0.6049	0.0058	0.5219	0.0
	146	147	147	147	147	146	147	147	147

Table A.3
Correlation matrix: Pa

Correlation Analysis

37 'VAR' Variables: TOTPA PERFMEAS CLIENTSO COMMUN PERFORIE PERSEVER EAGERNES IDSOLPRO CSISP CSCSO CSPERF CSPERS CCSQISP CCSQEL CCSQHI CCSQCSO CCSQCOMM CCSQISEN CCSQCOOP CCSQPERF CCSQPERS CCSQSELF VERBISP VERBHI CHECKHI CLASSHI NUMISP TOTISP TOTEL TOTHI TOTCSO TOTCOMM TOTISEN TOTCOOP TOTPERF TOTPERS TOTSELF

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
TOTPA	125	268.304000	58.797935	33538	83.000000	374.000000
PERFMEAS	133	66.318647	27.313420	8820.380000	4.000000	114.450000
CLIENTSO	125	51.000000	13.127170	6375.000000	12.000000	70.000000
COMMUN	125	59.280000	13.104173	7410.000000	18.000000	80.000000
PERFORIE	125	29.192000	7.700750	3649.000000	3.000000	40.000000
PERSEVER	125	32.456000	7.304996	4057.000000	9.000000	45.000000
EAGERNES	124	31.604839	8.712964	3919.000000	7.000000	45.000000
IDSOLPRO	124	65.548387	15.883394	8128.000000	6.000000	95.000000
CSISP	140	1.914286	0.877256	268.000000	1.000000	4.000000
CSCSO	121	1.818182	0.885061	220.000000	1.000000	4.000000
CSPERF	140	1.700000	0.792955	238.000000	1.000000	4.000000
CSPERS	140	1.692857	0.838776	237.000000	1.000000	4.000000
CCSQISP	140	3.171429	1.024469	444.000000	1.000000	5.000000
CCSQEL	140	3.521429	0.790846	493.000000	1.000000	5.000000
CCSQHI	140	3.614286	0.827458	506.000000	1.000000	5.000000
CCSQCSO	140	3.714286	0.915775	520.000000	1.000000	5.000000
CCSQCOMM	140	2.442857	1.088008	342.000000	1.000000	5.000000
CCSQISEN	140	3.407143	0.958839	477.000000	1.000000	5.000000
CCSQCOOP	140	3.614286	1.007781	506.000000	1.000000	5.000000
CCSQPERF	140	3.392857	0.837059	475.000000	1.000000	5.000000
CCSQPERS	140	2.964286	0.884810	415.000000	1.000000	5.000000
CCSQSELF	140	3.028571	0.856149	424.000000	1.000000	5.000000
VERBISP	140	29.257143	21.367417	4096.000000	1.000000	88.000000
VERBHI	139	29.618705	22.869635	4117.000000	1.000000	86.000000
CHECKHI	140	65.578571	22.475588	9181.000000	4.000000	99.000000
CLASSHI	140	51.992857	21.334437	7279.000000	2.000000	98.000000
NUMISP	140	40.542857	21.855435	5676.000000	2.000000	96.000000
TOTISP	140	2.264286	0.773767	317.000000	1.000000	4.000000
TOTEL	140	3.514286	0.817838	492.000000	1.000000	5.000000
TOTHI	140	3.457143	0.692939	484.000000	2.000000	5.000000
TOTCSO	140	2.378571	0.955618	333.000000	1.000000	5.000000
TOTCOMM	140	2.121429	0.885274	297.000000	1.000000	5.000000
TOTISEN	140	2.785714	1.023365	390.000000	1.000000	5.000000
TOTCOOP	140	3.578571	1.053038	501.000000	1.000000	5.000000
TOTPERF	138	2.065217	0.821309	285.000000	1.000000	5.000000
TOTPERS	138	1.876812	0.841036	259.000000	1.000000	4.000000
TOTSELF	137	2.766423	0.964539	379.000000	1.000000	5.000000

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTPA	PERFMEAS	CLIENTSO	COMMUN	PERFORIE	PERSEVER	EAGERNES	IDSOLPRO	CSISP	CSCSO
TOTPA	1.00000	0.18286	0.91762	0.89692	0.82300	0.87449	0.78747	0.92610	0.04047	0.05298
	0.0	0.0429	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.6540	0.5878
	125	123	125	125	125	125	124	124	125	107
PERFMEAS	0.18286	1.00000	0.05635	0.06947	0.36171	0.24389	0.15872	0.14388	0.16505	0.15798
	0.0429	0.0	0.5359	0.4452	0.0001	0.0066	0.0808	0.1139	0.0576	0.0932
	123	133	123	123	123	123	122	122	133	114
CLIENTSO	0.91762	0.05635	1.00000	0.85070	0.70227	0.77244	0.63624	0.81510	0.07502	0.06607
	0.0001	0.5359	0.0	0.0001	0.0001	0.0001	0.0001	0.0001	0.4057	0.4990
	125	123	125	125	125	125	124	124	125	107
COMMUN	0.89692	0.06947	0.85070	1.00000	0.63112	0.72014	0.63351	0.79886	0.08232	0.09562
	0.0001	0.4452	0.0001	0.0	0.0001	0.0001	0.0001	0.0001	0.3614	0.3272
	125	123	125	125	125	125	124	124	125	107
PERFORIE	0.82300	0.36171	0.70227	0.63112	1.00000	0.77529	0.69236	0.71505	-0.02405	0.06198
	0.0001	0.0001	0.0001	0.0001	0.0	0.0001	0.0001	0.0001	0.7901	0.5259
	125	123	125	125	125	125	124	124	125	107
PERSEVER	0.87449	0.24389	0.77244	0.72014	0.77529	1.00000	0.68848	0.78272	-0.00020	0.03385
	0.0001	0.0066	0.0001	0.0001	0.0001	0.0	0.0001	0.0001	0.9982	0.7293
	125	123	125	125	125	125	124	124	125	107
EAGERNES	0.78747	0.15872	0.63624	0.63351	0.69236	0.68848	1.00000	0.66133	0.03276	0.03173
	0.0001	0.0808	0.0001	0.0001	0.0001	0.0001	0.0	0.0001	0.7180	0.7468
	124	122	124	124	124	124	124	123	124	106
IDSOLPRO	0.92610	0.14388	0.81510	0.79886	0.71505	0.78272	0.66133	1.00000	0.03912	0.03411
	0.0001	0.1139	0.0001	0.0001	0.0001	0.0001	0.0001	0.0	0.6662	0.7285
	124	122	124	124	124	124	123	124	124	106
CSISP	0.04047	0.16505	0.07502	0.08232	-0.02405	-0.00020	0.03276	0.03912	1.00000	0.70042
	0.6540	0.0576	0.4057	0.3614	0.7901	0.9982	0.7180	0.6662	0.0	0.0001
	125	133	125	125	125	125	124	124	140	121
CSCSO	0.05298	0.15798	0.06607	0.09562	0.06198	0.03385	0.03173	0.03411	0.70042	1.00000
	0.5878	0.0932	0.4990	0.3272	0.5259	0.7293	0.7468	0.7285	0.0001	0.0
	107	114	107	107	107	107	106	106	121	121
CSPERF	0.02835	0.22132	0.04583	0.03539	-0.01871	0.00376	0.06705	0.00772	0.73843	0.63907
	0.7536	0.0105	0.6118	0.6952	0.8359	0.9668	0.4593	0.9322	0.0001	0.0001
	125	133	125	125	125	125	124	124	140	121
CSPERS	0.10169	0.27303	0.12070	0.09420	0.07369	0.09024	0.07694	0.08080	0.75591	0.78934
	0.2592	0.0015	0.1800	0.2961	0.4141	0.3169	0.3957	0.3724	0.0001	0.0001
	125	133	125	125	125	125	124	124	140	121
CCSQISP	0.09713	0.05769	0.07637	0.04185	0.15177	0.09937	0.15264	-0.01801	-0.07959	-0.10124
	0.2812	0.5095	0.3973	0.6431	0.0911	0.2702	0.0906	0.8426	0.3499	0.2692
	125	133	125	125	125	125	124	124	140	121

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTPA	PERFMEAS	CLIENTSO	COMMUN	PERFORIE	PERSEVER	EAGERNES	IDSOLPRO	CSISP	CSCSO
CCSQEL	0.11695	0.04171	0.13793	0.03433	0.16616	0.14500	0.15745	0.04403	-0.03881	-0.13400
	0.1940	0.6336	0.1250	0.7039	0.0640	0.1067	0.0807	0.6273	0.6489	0.1428
	125	133	125	125	125	125	124	124	140	121
CCSQHI	0.20689	0.21107	0.18522	0.05425	0.28582	0.31105	0.20179	0.13661	0.00368	-0.12685
	0.0206	0.0147	0.0386	0.5479	0.0012	0.0004	0.0246	0.1303	0.9656	0.1656
	125	133	125	125	125	125	124	124	140	121
CCSQCSO	0.00779	0.03516	0.10652	-0.02817	-0.00271	0.00214	-0.07292	-0.06033	-0.02175	-0.10893
	0.9313	0.6878	0.2371	0.7551	0.9761	0.9811	0.4209	0.5056	0.7987	0.2343
	125	133	125	125	125	125	124	124	140	121
CCSQCOMM	-0.14985	-0.12148	-0.10673	-0.13467	-0.16309	-0.16258	-0.10511	-0.16686	-0.15592	-0.10496
	0.0953	0.1636	0.2361	0.1343	0.0692	0.0701	0.2453	0.0640	0.0658	0.2519
	125	133	125	125	125	125	124	124	140	121
CCSQISEN	-0.07077	-0.04079	0.00586	-0.04538	-0.12764	-0.10498	-0.11133	-0.09984	-0.11217	-0.10904
	0.4329	0.6411	0.9483	0.6153	0.1561	0.2440	0.2183	0.2699	0.1870	0.2338
	125	133	125	125	125	125	124	124	140	121
CCSQCOOP	-0.28358	-0.01136	-0.24981	-0.22931	-0.31129	-0.29035	-0.27621	-0.27051	-0.10277	-0.08470
	0.0014	0.8967	0.0050	0.0101	0.0004	0.0010	0.0019	0.0024	0.2270	0.3556
	125	133	125	125	125	125	124	124	140	121
CCSQPERF	0.22585	0.23336	0.24557	0.10371	0.30943	0.31119	0.17385	0.15519	0.01680	-0.06340
	0.0113	0.0069	0.0058	0.2498	0.0004	0.0004	0.0535	0.0852	0.8439	0.4897
	125	133	125	125	125	125	124	124	140	121
CCSQPERS	0.09874	0.16858	0.11037	0.06468	0.10514	0.13719	0.02456	0.02367	0.00530	0.05561
	0.2733	0.0524	0.2205	0.4736	0.2432	0.1271	0.7866	0.7942	0.9505	0.5446
	125	133	125	125	125	125	124	124	140	121
CCSQSELF	-0.01720	0.03425	-0.01816	0.02829	-0.01826	-0.03364	0.01954	-0.04163	-0.03503	-0.09424
	0.8490	0.6955	0.8407	0.7541	0.8398	0.7096	0.8294	0.6462	0.6811	0.3039
	125	133	125	125	125	125	124	124	140	121
VERBISP	0.09873	-0.09993	0.14134	0.08230	0.14817	0.00017	0.07422	0.05224	0.07219	-0.05029
	0.2733	0.2524	0.1159	0.3615	0.0991	0.9985	0.4127	0.5645	0.3967	0.5838
	125	133	125	125	125	125	124	124	140	121
VERBHI	-0.02583	-0.00626	-0.04737	0.02377	0.04817	-0.03974	0.06834	-0.04537	0.14518	0.04744
	0.7758	0.9432	0.6013	0.7932	0.5952	0.6612	0.4526	0.6183	0.0882	0.6069
	124	132	124	124	124	124	123	123	139	120
CHECKHI	0.27040	0.04289	0.25732	0.17110	0.33004	0.30027	0.24732	0.23697	0.04997	-0.05912
	0.0023	0.6240	0.0038	0.0564	0.0002	0.0007	0.0056	0.0081	0.5577	0.5195
	125	133	125	125	125	125	124	124	140	121
CLASSHI	0.24927	0.13063	0.22906	0.22144	0.27949	0.26098	0.22493	0.14845	0.06916	0.04247
	0.0051	0.1340	0.0102	0.0131	0.0016	0.0033	0.0120	0.0999	0.4168	0.6437
	125	133	125	125	125	125	124	124	140	121

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTPA	PERFMEAS	CLIENTSO	COMMUN	PERFORIE	PERSEVER	EAGERNES	IDSOLPRO	CSISP	CSCSO
NUMISP	0.19641	-0.10120	0.24651	0.12258	0.10826	0.16843	0.27452	0.13996	0.19681	-0.00350
	0.0281	0.2464	0.0056	0.1732	0.2294	0.0604	0.0020	0.1210	0.0198	0.9696
	125	133	125	125	125	125	124	124	140	121
TOTISP	0.05385	0.05600	0.10979	0.03312	0.03514	0.00827	0.00193	0.10588	0.70132	0.52991
	0.5509	0.5221	0.2229	0.7139	0.6972	0.9271	0.9830	0.2418	0.0001	0.0001
	125	133	125	125	125	125	124	124	140	121
TOTEL	0.11284	0.04907	0.13523	0.03145	0.16524	0.14732	0.14072	0.04209	-0.02836	-0.12146
	0.2102	0.5749	0.1327	0.7277	0.0655	0.1011	0.1190	0.6426	0.7394	0.1845
	125	133	125	125	125	125	124	124	140	121
TOTHI	0.13041	0.02651	0.17910	0.08354	0.20736	0.19772	0.10792	0.02983	0.11226	0.01332
	0.1472	0.7620	0.0457	0.3543	0.0203	0.0271	0.2329	0.7423	0.1866	0.8847
	125	133	125	125	125	125	124	124	140	121
TOTCSO	0.07720	0.12564	0.09673	0.12211	-0.03061	0.04015	0.02369	0.08596	0.45091	0.71322
	0.3921	0.1496	0.2832	0.1749	0.7347	0.6566	0.7939	0.3425	0.0001	0.0001
	125	133	125	125	125	125	124	124	140	121
TOTCOMM	-0.02565	-0.05532	0.01457	-0.02030	-0.07201	-0.06713	0.00937	-0.03641	0.07834	0.04829
	0.7765	0.5271	0.8719	0.8222	0.4248	0.4570	0.9177	0.6881	0.3575	0.5989
	125	133	125	125	125	125	124	124	140	121
TOTISEN	-0.03865	-0.05176	-0.03567	-0.01427	-0.11283	-0.09420	0.00425	-0.01238	0.09158	0.10816
	0.6687	0.5540	0.6929	0.8745	0.2103	0.2961	0.9626	0.8915	0.2818	0.2376
	125	133	125	125	125	125	124	124	140	121
TOTCOOP	-0.31290	-0.04833	-0.27775	-0.25189	-0.33659	-0.32040	-0.27836	-0.30797	-0.06275	-0.06259
	0.0004	0.5806	0.0017	0.0046	0.0001	0.0003	0.0017	0.0005	0.4614	0.4953
	125	133	125	125	125	125	124	124	140	121
TOTPERF	0.16453	0.20181	0.18441	0.14539	0.04014	0.14222	0.09811	0.17525	0.53233	0.46082
	0.0678	0.0203	0.0403	0.1071	0.6580	0.1151	0.2803	0.0525	0.0001	0.0001
	124	132	124	124	124	124	123	123	138	119
TOTPERS	0.18642	0.28113	0.19107	0.15612	0.15248	0.19579	0.07763	0.18666	0.65718	0.70496
	0.0382	0.0011	0.0335	0.0834	0.0909	0.0293	0.3934	0.0387	0.0001	0.0001
	124	132	124	124	124	124	123	123	138	119
TOTSELF	0.04741	0.05228	0.01651	0.07469	-0.07835	-0.03676	0.14375	0.08804	0.19638	0.15626
	0.6026	0.5532	0.8561	0.4116	0.3890	0.6864	0.1142	0.3349	0.0215	0.0911
	123	131	123	123	123	123	122	122	137	118

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CSPERF	CSPERS	CCSQISP	CCSQEL	CCSQHI	CCSQCSO	CCSQCOMM	CCSQISEN	CCSQCOOP	CCSQPERF
TOTPA	0.02835	0.10169	0.09713	0.11695	0.20689	0.00779	-0.14985	-0.07077	-0.28358	0.22585
	0.7536	0.2592	0.2812	0.1940	0.0206	0.9313	0.0953	0.4329	0.0014	0.0113
	125	125	125	125	125	125	125	125	125	125
PERFMEAS	0.22132	0.27303	0.05769	0.04171	0.21107	0.03516	-0.12148	-0.04079	-0.01136	0.23336
	0.0105	0.0015	0.5095	0.6336	0.0147	0.6878	0.1636	0.6411	0.8967	0.0069
	133	133	133	133	133	133	133	133	133	133
CLIENTSO	0.04583	0.12070	0.07637	0.13793	0.18522	0.10652	-0.10673	0.00586	-0.24981	0.24557
	0.6118	0.1800	0.3973	0.1250	0.0386	0.2371	0.2361	0.9483	0.0050	0.0058
	125	125	125	125	125	125	125	125	125	125
COMMUN	0.03539	0.09420	0.04185	0.03433	0.05425	-0.02817	-0.13467	-0.04538	-0.22931	0.10371
	0.6952	0.2961	0.6431	0.7039	0.5479	0.7551	0.1343	0.6153	0.0101	0.2498
	125	125	125	125	125	125	125	125	125	125
PERFORIE	-0.01871	0.07369	0.15177	0.16616	0.28582	-0.00271	-0.16309	-0.12764	-0.31129	0.30943
	0.8359	0.4141	0.0911	0.0640	0.0012	0.9761	0.0692	0.1561	0.0004	0.0004
	125	125	125	125	125	125	125	125	125	125
PERSEVER	0.00376	0.09024	0.09937	0.14500	0.31105	0.00214	-0.16258	-0.10498	-0.29035	0.31119
	0.9668	0.3169	0.2702	0.1067	0.0004	0.9811	0.0701	0.2440	0.0010	0.0004
	125	125	125	125	125	125	125	125	125	125
EAGERNES	0.06705	0.07694	0.15264	0.15745	0.20179	-0.07292	-0.10511	-0.11133	-0.27621	0.17385
	0.4593	0.3957	0.0906	0.0807	0.0246	0.4209	0.2453	0.2183	0.0019	0.0535
	124	124	124	124	124	124	124	124	124	124
IDSOLPRO	0.00772	0.08080	-0.01801	0.04403	0.13661	-0.06033	-0.16686	-0.09984	-0.27051	0.15519
	0.9322	0.3724	0.8426	0.6273	0.1303	0.5056	0.0640	0.2699	0.0024	0.0852
	124	124	124	124	124	124	124	124	124	124
CSISP	0.73843	0.75591	-0.07959	-0.03881	0.00368	-0.02175	-0.15592	-0.11217	-0.10277	0.01680
	0.0001	0.0001	0.3499	0.6489	0.9656	0.7987	0.0658	0.1870	0.2270	0.8439
	140	140	140	140	140	140	140	140	140	140
CSCSO	0.63907	0.78934	-0.10124	-0.13400	-0.12685	-0.10893	-0.10496	-0.10904	-0.08470	-0.06340
	0.0001	0.0001	0.2692	0.1428	0.1656	0.2343	0.2519	0.2338	0.3556	0.4897
	121	121	121	121	121	121	121	121	121	121
CSPERF	1.00000	0.77988	0.01063	-0.02409	-0.00219	-0.01981	-0.11174	-0.08421	-0.07382	0.03794
	0.0	0.0001	0.9008	0.7775	0.9795	0.8163	0.1887	0.3225	0.3860	0.6563
	140	140	140	140	140	140	140	140	140	140
CSPERS	0.77988	1.00000	-0.12247	-0.10388	-0.09936	-0.16190	-0.18886	-0.16542	-0.16669	-0.07282
	0.0001	0.0	0.1494	0.2219	0.2428	0.0560	0.0254	0.0508	0.0490	0.3925
	140	140	140	140	140	140	140	140	140	140
CCSQISP	0.01063	-0.12247	1.00000	0.78572	0.43501	0.01424	0.07985	-0.13016	-0.13060	0.43265
	0.9008	0.1494	0.0	0.0001	0.0001	0.8674	0.3483	0.1253	0.1240	0.0001
	140	140	140	140	140	140	140	140	140	140

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CSPERF	CSPERS	CCSQISP	CCSQEL	CCSQHI	CCSQCSO	CCSQCOMM	CCSQISEN	CCSQCOOP	CCSQPERF
CCSQEL	-0.02409	-0.10388	0.78572	1.00000	0.61738	0.06812	-0.05291	-0.15864	-0.22425	0.56861
	0.7775	0.2219	0.0001	0.0	0.0001	0.4239	0.5347	0.0612	0.0077	0.0001
	140	140	140	140	140	140	140	140	140	140
CCSQHI	-0.00219	-0.09936	0.43501	0.61738	1.00000	0.20480	-0.24841	-0.19962	-0.27459	0.80201
	0.9795	0.2428	0.0001	0.0001	0.0	0.0152	0.0031	0.0181	0.0010	0.0001
	140	140	140	140	140	140	140	140	140	140
CCSQCSO	-0.01981	-0.16190	0.01424	0.06812	0.20480	1.00000	0.30120	0.67418	0.51894	0.32580
	0.8163	0.0560	0.8674	0.4239	0.0152	0.0	0.0003	0.0001	0.0001	0.0001
	140	140	140	140	140	140	140	140	140	140
CCSQCOMM	-0.11174	-0.18886	0.07985	-0.05291	-0.24841	0.30120	1.00000	0.60519	0.48497	-0.14501
	0.1887	0.0254	0.3483	0.5347	0.0031	0.0003	0.0	0.0001	0.0001	0.0874
	140	140	140	140	140	140	140	140	140	140
CCSQISEN	-0.08421	-0.16542	-0.13016	-0.15864	-0.19962	0.67418	0.60519	1.00000	0.71463	-0.06627
	0.3225	0.0508	0.1253	0.0612	0.0181	0.0001	0.0001	0.0	0.0001	0.4366
	140	140	140	140	140	140	140	140	140	140
CCSQCOOP	-0.07382	-0.16669	-0.13060	-0.22425	-0.27459	0.51894	0.48497	0.71463	1.00000	-0.18580
	0.3860	0.0490	0.1240	0.0077	0.0010	0.0001	0.0001	0.0001	0.0	0.0280
	140	140	140	140	140	140	140	140	140	140
CCSQPERF	0.03794	-0.07282	0.43265	0.56861	0.80201	0.32580	-0.14501	-0.06627	-0.18580	1.00000
	0.6563	0.3925	0.0001	0.0001	0.0001	0.0001	0.0874	0.4366	0.0280	0.0
	140	140	140	140	140	140	140	140	140	140
CCSQPERS	0.05640	-0.00519	0.49887	0.41749	0.43306	0.28031	0.20338	0.04270	-0.03170	0.58247
	0.5081	0.9514	0.0001	0.0001	0.0001	0.0008	0.0160	0.6164	0.7101	0.0001
	140	140	140	140	140	140	140	140	140	140
CCSQSELF	0.01272	-0.17804	0.15842	0.03097	-0.06557	0.31329	0.27980	0.33628	0.41310	0.07457
	0.8815	0.0353	0.0616	0.7165	0.4414	0.0002	0.0008	0.0001	0.0001	0.3812
	140	140	140	140	140	140	140	140	140	140
VERBISP	0.04492	0.02692	0.12582	0.15890	0.08703	0.01886	-0.05011	-0.02165	-0.10428	0.02770
	0.5982	0.7522	0.1385	0.0608	0.3066	0.8250	0.5565	0.7996	0.2202	0.7453
	140	140	140	140	140	140	140	140	140	140
VERBHI	0.13311	0.13206	-0.08533	-0.02965	-0.01130	-0.03416	-0.06456	0.00518	0.02740	-0.08117
	0.1183	0.1212	0.3179	0.7289	0.8950	0.6897	0.4502	0.9517	0.7488	0.3422
	139	139	139	139	139	139	139	139	139	139
CHECKHI	-0.01522	-0.04546	0.14657	0.15249	0.31034	0.02731	-0.05968	-0.01635	-0.30801	0.23716
	0.8584	0.5938	0.0840	0.0721	0.0002	0.7487	0.4836	0.8479	0.0002	0.0048
	140	140	140	140	140	140	140	140	140	140
CLASSHI	0.04452	0.05294	0.07510	0.08337	0.08787	0.16228	0.04787	0.08736	0.00824	0.09966
	0.6014	0.5344	0.3778	0.3274	0.3019	0.0554	0.5744	0.3047	0.9231	0.2414
	140	140	140	140	140	140	140	140	140	140

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CSPERF	CSPERS	CCSQISP	CCSQEL	CCSQHI	CCSQCSO	CCSQCOMM	CCSQISEN	CCSQCOOP	CCSQPERF
NUMISP	0.09664	0.09668	0.06072	0.15707	0.12225	0.06136	-0.05405	-0.04873	-0.09985	0.04921
	0.2560	0.2558	0.4761	0.0638	0.1502	0.4714	0.5259	0.5675	0.2405	0.5637
	140	140	140	140	140	140	140	140	140	140
TOTISP	0.54054	0.58045	-0.06664	-0.00344	-0.00819	-0.06527	-0.11439	-0.08789	-0.13588	0.00516
	0.0001	0.0001	0.4340	0.9678	0.9235	0.4436	0.1784	0.3018	0.1094	0.9518
	140	140	140	140	140	140	140	140	140	140
TOTEL	-0.01553	-0.10368	0.76126	0.98392	0.64606	0.11115	-0.04759	-0.14050	-0.21149	0.58550
	0.8555	0.2228	0.0001	0.0001	0.0001	0.1911	0.5766	0.0978	0.0121	0.0001
	140	140	140	140	140	140	140	140	140	140
TOTHI	0.06808	0.11953	0.10163	0.19204	0.24700	0.05992	-0.09870	-0.01145	-0.13716	0.14707
	0.4241	0.1595	0.2321	0.0230	0.0033	0.4819	0.2460	0.8932	0.1061	0.0829
	140	140	140	140	140	140	140	140	140	140
TOTCSO	0.42628	0.49615	-0.16965	-0.13932	-0.12335	0.05872	-0.01018	0.10538	0.10042	-0.07034
	0.0001	0.0001	0.0451	0.1006	0.1465	0.4907	0.9050	0.2153	0.2378	0.4089
	140	140	140	140	140	140	140	140	140	140
TOTCOMM	0.15475	0.00215	-0.03105	-0.08081	-0.12220	0.14072	0.40686	0.33121	0.27866	-0.04542
	0.0679	0.9799	0.7157	0.3425	0.1503	0.0973	0.0001	0.0001	0.0009	0.5941
	140	140	140	140	140	140	140	140	140	140
TOTISEN	0.19504	0.05687	-0.04705	-0.02095	-0.05583	0.19520	0.14400	0.32417	0.24714	-0.01860
	0.0209	0.5045	0.5809	0.8059	0.5124	0.0208	0.0896	0.0001	0.0032	0.8274
	140	140	140	140	140	140	140	140	140	140
TOTCOOP	-0.04049	-0.14760	-0.12594	-0.20073	-0.22918	0.51582	0.44036	0.67704	0.95751	-0.18626
	0.6348	0.0818	0.1381	0.0174	0.0065	0.0001	0.0001	0.0001	0.0001	0.0276
	140	140	140	140	140	140	140	140	140	140
TOTPERF	0.74436	0.58759	-0.05738	-0.04334	0.00220	0.05290	-0.08917	-0.00726	-0.03251	0.07831
	0.0001	0.0001	0.5038	0.6137	0.9796	0.5378	0.2983	0.9326	0.7050	0.3613
	138	138	138	138	138	138	138	138	138	138
TOTPERS	0.65358	0.86067	-0.10074	-0.07616	-0.05530	-0.12011	-0.16248	-0.16183	-0.17530	-0.01146
	0.0001	0.0001	0.2397	0.3747	0.5195	0.1606	0.0569	0.0579	0.0397	0.8938
	138	138	138	138	138	138	138	138	138	138
TOTSELF	0.23593	0.12800	-0.01775	-0.04798	-0.04275	0.07265	-0.02951	0.07398	0.10661	-0.00140
	0.0055	0.1361	0.8369	0.5777	0.6199	0.3989	0.7321	0.3903	0.2150	0.9871
	137	137	137	137	137	137	137	137	137	137

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CCSQPERS	CCSQSELF	VERBISP	VERBHI	CHECKHI	CLASSHI	NUMISP	TOTISP	TOTEL	TOTHI
TOTPA	0.09874	-0.01720	0.09873	-0.02583	0.27040	0.24927	0.19641	0.05385	0.11284	0.13041
	0.2733	0.8490	0.2733	0.7758	0.0023	0.0051	0.0281	0.5509	0.2102	0.1472
	125	125	125	124	125	125	125	125	125	125
PERFMEAS	0.16858	0.03425	-0.09993	-0.00626	0.04289	0.13063	-0.10120	0.05600	0.04907	0.02651
	0.0524	0.6955	0.2524	0.9432	0.6240	0.1340	0.2464	0.5221	0.5749	0.7620
	133	133	133	132	133	133	133	133	133	133
CLIENTSO	0.11037	-0.01816	0.14134	-0.04737	0.25732	0.22906	0.24651	0.10979	0.13523	0.17910
	0.2205	0.8407	0.1159	0.6013	0.0038	0.0102	0.0056	0.2229	0.1327	0.0457
	125	125	125	124	125	125	125	125	125	125
COMMUN	0.06468	0.02829	0.08230	0.02377	0.17110	0.22144	0.12258	0.03312	0.03145	0.08354
	0.4736	0.7541	0.3615	0.7932	0.0564	0.0131	0.1732	0.7139	0.7277	0.3543
	125	125	125	124	125	125	125	125	125	125
PERFORIE	0.10514	-0.01826	0.14817	0.04817	0.33004	0.27949	0.10826	0.03514	0.16524	0.20736
	0.2432	0.8398	0.0991	0.5952	0.0002	0.0016	0.2294	0.6972	0.0655	0.0203
	125	125	125	124	125	125	125	125	125	125
PERSEVER	0.13719	-0.03364	0.00017	-0.03974	0.30027	0.26098	0.16843	0.00827	0.14732	0.19772
	0.1271	0.7096	0.9985	0.6612	0.0007	0.0033	0.0604	0.9271	0.1011	0.0271
	125	125	125	124	125	125	125	125	125	125
EAGERNES	0.02456	0.01954	0.07422	0.06834	0.24732	0.22493	0.27452	0.00193	0.14072	0.10792
	0.7866	0.8294	0.4127	0.4526	0.0056	0.0120	0.0020	0.9830	0.1190	0.2329
	124	124	124	123	124	124	124	124	124	124
IDSOLPRO	0.02367	-0.04163	0.05224	-0.04537	0.23697	0.14845	0.13996	0.10588	0.04209	0.02983
	0.7942	0.6462	0.5645	0.6183	0.0081	0.0999	0.1210	0.2418	0.6426	0.7423
	124	124	124	123	124	124	124	124	124	124
CSISP	0.00530	-0.03503	0.07219	0.14518	0.04997	0.06916	0.19681	0.70132	-0.02836	0.11226
	0.9505	0.6811	0.3967	0.0882	0.5577	0.4168	0.0198	0.0001	0.7394	0.1866
	140	140	140	139	140	140	140	140	140	140
CSCSO	0.05561	-0.09424	-0.05029	0.04744	-0.05912	0.04247	-0.00350	0.52991	-0.12146	0.01332
	0.5446	0.3039	0.5838	0.6069	0.5195	0.6437	0.9696	0.0001	0.1845	0.8847
	121	121	121	120	121	121	121	121	121	121
CSPERF	0.05640	0.01272	0.04492	0.13311	-0.01522	0.04452	0.09664	0.54054	-0.01553	0.06808
	0.5081	0.8815	0.5982	0.1183	0.8584	0.6014	0.2560	0.0001	0.8555	0.4241
	140	140	140	139	140	140	140	140	140	140
CSPERS	-0.00519	-0.17804	0.02692	0.13206	-0.04546	0.05294	0.09668	0.58045	-0.10368	0.11953
	0.9514	0.0353	0.7522	0.1212	0.5938	0.5344	0.2558	0.0001	0.2228	0.1595
	140	140	140	139	140	140	140	140	140	140
CCSQISP	0.49887	0.15842	0.12582	-0.08533	0.14657	0.07510	0.06072	-0.06664	0.76126	0.10163
	0.0001	0.0616	0.1385	0.3179	0.0840	0.3778	0.4761	0.4340	0.0001	0.2321
	140	140	140	139	140	140	140	140	140	140

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CCSQPERS	CCSQSELF	VERBISP	VERBHI	CHECKHI	CLASSHI	NUMISP	TOTISP	TOTEL	TOTHI
CCSQEL	0.41749	0.03097	0.15890	-0.02965	0.15249	0.08337	0.15707	-0.00344	0.98392	0.19204
	0.0001	0.7165	0.0608	0.7289	0.0721	0.3274	0.0638	0.9678	0.0001	0.0230
	140	140	140	139	140	140	140	140	140	140
CCSQHI	0.43306	-0.06557	0.08703	-0.01130	0.31034	0.08787	0.12225	-0.00819	0.64606	0.24700
	0.0001	0.4414	0.3066	0.8950	0.0002	0.3019	0.1502	0.9235	0.0001	0.0033
	140	140	140	139	140	140	140	140	140	140
CCSQCSO	0.28031	0.31329	0.01886	-0.03416	0.02731	0.16228	0.06136	-0.06527	0.11115	0.05992
	0.0008	0.0002	0.8250	0.6897	0.7487	0.0554	0.4714	0.4436	0.1911	0.4819
	140	140	140	139	140	140	140	140	140	140
CCSQCOMM	0.20338	0.27980	-0.05011	-0.06456	-0.05968	0.04787	-0.05405	-0.11439	-0.04759	-0.09870
	0.0160	0.0008	0.5565	0.4502	0.4836	0.5744	0.5259	0.1784	0.5766	0.2460
	140	140	140	139	140	140	140	140	140	140
CCSQISEN	0.04270	0.33628	-0.02165	0.00518	-0.01635	0.08736	-0.04873	-0.08789	-0.14050	-0.01145
	0.6164	0.0001	0.7996	0.9517	0.8479	0.3047	0.5675	0.3018	0.0978	0.8932
	140	140	140	139	140	140	140	140	140	140
CCSQCOOP	-0.03170	0.41310	-0.10428	0.02740	-0.30801	0.00824	-0.09985	-0.13588	-0.21149	-0.13716
	0.7101	0.0001	0.2202	0.7488	0.0002	0.9231	0.2405	0.1094	0.0121	0.1061
	140	140	140	139	140	140	140	140	140	140
CCSQPERF	0.58247	0.07457	0.02770	-0.08117	0.23716	0.09966	0.04921	0.00516	0.58550	0.14707
	0.0001	0.3812	0.7453	0.3422	0.0048	0.2414	0.5637	0.9518	0.0001	0.0829
	140	140	140	139	140	140	140	140	140	140
CCSQPERS	1.00000	0.23878	-0.06001	-0.12432	0.17144	0.10632	-0.09200	-0.01764	0.42324	0.08549
	0.0	0.0045	0.4812	0.1448	0.0428	0.2112	0.2797	0.8361	0.0001	0.3152
	140	140	140	139	140	140	140	140	140	140
CCSQSELF	0.23878	1.00000	0.01965	0.00904	0.08886	0.02207	0.07337	-0.05492	0.01996	-0.04643
	0.0045	0.0	0.8177	0.9158	0.2964	0.7958	0.3890	0.5193	0.8149	0.5860
	140	140	140	139	140	140	140	140	140	140
VERBISP	-0.06001	0.01965	1.00000	0.33727	0.29974	0.27943	0.39366	0.14294	0.16981	0.30200
	0.4812	0.8177	0.0	0.0001	0.0003	0.0008	0.0001	0.0920	0.0449	0.0003
	140	140	140	139	140	140	140	140	140	140
VERBHI	-0.12432	0.00904	0.33727	1.00000	0.17535	0.13940	0.07918	0.12711	-0.00872	0.18135
	0.1448	0.9158	0.0001	0.0	0.0389	0.1017	0.3542	0.1359	0.9189	0.0326
	139	139	139	139	139	139	139	139	139	139
CHECKHI	0.17144	0.08886	0.29974	0.17535	1.00000	0.34317	0.28086	0.11359	0.18565	0.57925
	0.0428	0.2964	0.0003	0.0389	0.0	0.0001	0.0008	0.1814	0.0281	0.0001
	140	140	140	139	140	140	140	140	140	140
CLASSHI	0.10632	0.02207	0.27943	0.13940	0.34317	1.00000	0.27328	0.05677	0.10535	0.66157
	0.2112	0.7958	0.0008	0.1017	0.0001	0.0	0.0011	0.5053	0.2154	0.0001
	140	140	140	139	140	140	140	140	140	140

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	CCSQPERS	CCSQSELF	VERBISP	VERBHI	CHECKHI	CLASSHI	NUMISP	TOTISP	TOTEL	TOTHI
NUMISP	-0.09200	0.07337	0.39366	0.07918	0.28086	0.27328	1.00000	0.12631	0.16982	0.35688
	0.2797	0.3890	0.0001	0.3542	0.0008	0.0011	0.0	0.1370	0.0449	0.0001
	140	140	140	139	140	140	140	140	140	140
TOTISP	-0.01764	-0.05492	0.14294	0.12711	0.11359	0.05677	0.12631	1.00000	0.01104	0.06824
	0.8361	0.5193	0.0920	0.1359	0.1814	0.5053	0.1370	0.0	0.8970	0.4231
	140	140	140	139	140	140	140	140	140	140
TOTEL	0.42324	0.01996	0.16981	-0.00872	0.18565	0.10535	0.16982	0.01104	1.00000	0.21690
	0.0001	0.8149	0.0449	0.9189	0.0281	0.2154	0.0449	0.8970	0.0	0.0101
	140	140	140	139	140	140	140	140	140	140
TOTHI	0.08549	-0.04643	0.30200	0.18135	0.57925	0.66157	0.35688	0.06824	0.21690	1.00000
	0.3152	0.5860	0.0003	0.0326	0.0001	0.0001	0.0001	0.4231	0.0101	0.0
	140	140	140	139	140	140	140	140	140	140
TOTCSO	-0.08600	-0.16280	-0.14221	-0.01712	-0.09502	-0.08703	0.00249	0.47668	-0.13124	-0.11113
	0.3124	0.0546	0.0937	0.8415	0.2641	0.3066	0.9767	0.0001	0.1222	0.1912
	140	140	140	139	140	140	140	140	140	140
TOTCOMM	0.05150	0.03336	-0.12375	-0.03683	-0.04550	0.08918	-0.07408	0.18387	-0.07694	-0.04423
	0.5457	0.6956	0.1452	0.6669	0.5935	0.2947	0.3844	0.0297	0.3662	0.6038
	140	140	140	139	140	140	140	140	140	140
TOTISEN	-0.00057	0.06452	-0.12413	-0.01640	-0.06995	-0.03072	-0.09094	0.24466	-0.02210	-0.10435
	0.9947	0.4489	0.1440	0.8480	0.4115	0.7187	0.2853	0.0036	0.7955	0.2198
	140	140	140	139	140	140	140	140	140	140
TOTCOOP	-0.05488	0.39648	-0.08372	0.02745	-0.29025	0.00499	-0.04375	-0.17135	-0.17256	-0.05944
	0.5196	0.0001	0.3254	0.7484	0.0005	0.9534	0.6077	0.0429	0.0415	0.4854
	140	140	140	139	140	140	140	140	140	140
TOTPERF	0.01263	-0.01374	0.05314	0.04534	0.02884	-0.00148	0.12358	0.58202	-0.03277	0.02232
	0.8831	0.8729	0.5359	0.5988	0.7370	0.9863	0.1487	0.0001	0.7028	0.7950
	138	138	138	137	138	138	138	138	138	138
TOTPERS	0.04408	-0.19611	0.12634	0.10559	0.08555	0.10907	0.12941	0.57016	-0.06376	0.14309
	0.6077	0.0212	0.1398	0.2195	0.3184	0.2029	0.1303	0.0001	0.4575	0.0941
	138	138	138	137	138	138	138	138	138	138
TOTSELF	0.05877	0.29367	-0.08268	0.02939	0.00212	-0.04805	0.04598	0.33514	-0.04573	-0.08420
	0.4951	0.0005	0.3368	0.7341	0.9804	0.5771	0.5936	0.0001	0.5957	0.3280
	137	137	137	136	137	137	137	137	137	137

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCSO	TOTCOMM	TOTISEN	TOTCOOP	TOTPERF	TOTPERS	TOTSELF
TOTPA	0.07720	-0.02565	-0.03865	-0.31290	0.16453	0.18642	0.04741
	0.3921	0.7765	0.6687	0.0004	0.0678	0.0382	0.6026
	125	125	125	125	124	124	123
PERFMEAS	0.12564	-0.05532	-0.05176	-0.04833	0.20181	0.28113	0.05228
	0.1496	0.5271	0.5540	0.5806	0.0203	0.0011	0.5532
	133	133	133	133	132	132	131
CLIENTSO	0.09673	0.01457	-0.03567	-0.27775	0.18441	0.19107	0.01651
	0.2832	0.8719	0.6929	0.0017	0.0403	0.0335	0.8561
	125	125	125	125	124	124	123
COMMUN	0.12211	-0.02030	-0.01427	-0.25189	0.14539	0.15612	0.07469
	0.1749	0.8222	0.8745	0.0046	0.1071	0.0834	0.4116
	125	125	125	125	124	124	123
PERFORIE	-0.03061	-0.07201	-0.11283	-0.33659	0.04014	0.15248	-0.07835
	0.7347	0.4248	0.2103	0.0001	0.6580	0.0909	0.3890
	125	125	125	125	124	124	123
PERSEVER	0.04015	-0.06713	-0.09420	-0.32040	0.14222	0.19579	-0.03676
	0.6566	0.4570	0.2961	0.0003	0.1151	0.0293	0.6864
	125	125	125	125	124	124	123
EAGERNES	0.02369	0.00937	0.00425	-0.27836	0.09811	0.07763	0.14375
	0.7939	0.9177	0.9626	0.0017	0.2803	0.3934	0.1142
	124	124	124	124	123	123	122
IDSOLPRO	0.08596	-0.03641	-0.01238	-0.30797	0.17525	0.18666	0.08804
	0.3425	0.6881	0.8915	0.0005	0.0525	0.0387	0.3349
	124	124	124	124	123	123	122
CSISP	0.45091	0.07834	0.09158	-0.06275	0.53233	0.65718	0.19638
	0.0001	0.3575	0.2818	0.4614	0.0001	0.0001	0.0215
	140	140	140	140	138	138	137
CSCSO	0.71322	0.04829	0.10816	-0.06259	0.46082	0.70496	0.15626
	0.0001	0.5989	0.2376	0.4953	0.0001	0.0001	0.0911
	121	121	121	121	119	119	118
CSPERF	0.42628	0.15475	0.19504	-0.04049	0.74436	0.65358	0.23593
	0.0001	0.0679	0.0209	0.6348	0.0001	0.0001	0.0055
	140	140	140	140	138	138	137
CSPERS	0.49615	0.00215	0.05687	-0.14760	0.58759	0.86067	0.12800
	0.0001	0.9799	0.5045	0.0818	0.0001	0.0001	0.1361
	140	140	140	140	138	138	137
CCSQISP	-0.16965	-0.03105	-0.04705	-0.12594	-0.05738	-0.10074	-0.01775
	0.0451	0.7157	0.5809	0.1381	0.5038	0.2397	0.8369
	140	140	140	140	138	138	137

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCSO	TOTCOMM	TOTISEN	TOTCOOP	TOTPERF	TOTPERS	TOTSELF
CCSQEL	-0.13932	-0.08081	-0.02095	-0.20073	-0.04334	-0.07616	-0.04798
	0.1006	0.3425	0.8059	0.0174	0.6137	0.3747	0.5777
	140	140	140	140	138	138	137
CCSQHI	-0.12335	-0.12220	-0.05583	-0.22918	0.00220	-0.05530	-0.04275
	0.1465	0.1503	0.5124	0.0065	0.9796	0.5195	0.6199
	140	140	140	140	138	138	137
CCSQCSO	0.05872	0.14072	0.19520	0.51582	0.05290	-0.12011	0.07265
	0.4907	0.0973	0.0208	0.0001	0.5378	0.1606	0.3989
	140	140	140	140	138	138	137
CCSQCOMM	-0.01018	0.40686	0.14400	0.44036	-0.08917	-0.16248	-0.02951
	0.9050	0.0001	0.0896	0.0001	0.2983	0.0569	0.7321
	140	140	140	140	138	138	137
CCSQISEN	0.10538	0.33121	0.32417	0.67704	-0.00726	-0.16183	0.07398
	0.2153	0.0001	0.0001	0.0001	0.9326	0.0579	0.3903
	140	140	140	140	138	138	137
CCSQCOOP	0.10042	0.27866	0.24714	0.95751	-0.03251	-0.17530	0.10661
	0.2378	0.0009	0.0032	0.0001	0.7050	0.0397	0.2150
	140	140	140	140	138	138	137
CCSQPERF	-0.07034	-0.04542	-0.01860	-0.18626	0.07831	-0,01146	-0.00140
	0.4089	0.5941	0.8274	0.0276	0.3613	0.8938	0.9871
	140	140	140	140	138	138	137
CCSQPERS	-0.08600	0.05150	-0.00057	-0.05488	0.01263	0.04408	0.05877
	0.3124	0.5457	0.9947	0.5196	0.8831	0.6077	0.4951
	140	140	140	140	138	138	137
CCSQSELF	-0.16280	0.03336	0.06452	0.39648	-0.01374	-0.19611	0.29367
	0.0546	0.6956	0.4489	0.0001	0.8729	0.0212	0.0005
	140	140	140	140	138	138	137
VERBISP	-0.14221	-0.12375	-0.12413	-0.08372	0.05314	0.12634	-0.08268
	0.0937	0.1452	0.1440	0.3254	0.5359	0.1398	0.3368
	140	140	140	140	138	138	137
VERBHI	-0.01712	-0.03683	-0.01640	0.02745	0.04534	0.10559	0.02939
	0.8415	0.6669	0.8480	0.7484	0.5988	0.2195	0.7341
	139	139	139	139	137	137	136
CHECKHI	-0.09502	-0.04550	-0.06995	-0.29025	0.02884	0.08555	0.00212
	0.2641	0.5935	0.4115	0.0005	0.7370	0.3184	0.9804
	140	140	140	140	138	138	137
CLASSHI	-0.08703	0.08918	-0.03072	0.00499	-0.00148	0.10907	-0.04805
	0.3066	0.2947	0.7187	0.9534	0.9863	0.2029	0.5771
	140	140	140	140	138	138	137

Table A.3
Correlation matrix: Pa

Correlation Analysis

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCSO	TOTCOMM	TOTISEN	TOTCOOP	TOTPERF	TOTPERS	TOTSELF
NUMISP	0.00249	-0.07408	-0.09094	-0.04375	0.12358	0.12941	0.04598
	0.9767	0.3844	0.2853	0.6077	0.1487	0.1303	0.5936
	140	140	140	140	138	138	137
TOTISP	0.47668	0.18387	0.24466	-0.17135	0.58202	0.57016	0.33514
	0.0001	0.0297	0.0036	0.0429	0.0001	0.0001	0.0001
	140	140	140	140	138	138	137
TOTEL	-0.13124	-0.07694	-0.02210	-0.17256	-0.03277	-0.06376	-0.04573
	0.1222	0.3662	0.7955	0.0415	0.7028	0.4575	0.5957
	140	140	140	140	138	138	137
TOTHI	-0.11113	-0.04423	-0.10435	-0.05944	0.02232	0.14309	-0.08420
	0.1912	0.6038	0.2198	0.4854	0.7950	0.0941	0.3280
	140	140	140	140	138	138	137
TOTCSO	1.00000	0.39598	0.42195	0.10964	0.60703	0.41929	0.35718
	0.0	0.0001	0.0001	0.1972	0.0001	0.0001	0.0001
	140	140	140	140	138	138	137
TOTCOMM	0.39598	1.00000	0.64039	0.24822	0.36773	-0.01855	0.44232
	0.0001	0.0	0.0001	0.0031	0.0001	0.8290	0.0001
	140	140	140	140	138	138	137
TOTISEN	0.42195	0.64039	1.00000	0.22269	0.33608	-0.00483	0.55668
	0.0001	0.0001	0.0	0.0082	0.0001	0.9552	0.0001
	140	140	140	140	138	138	137
TOTCOOP	0.10964	0.24822	0.22269	1.00000	-0.03006	-0.19962	0.10661
	0.1972	0.0031	0.0082	0.0	0.7263	0.0189	0.2150
	140	140	140	140	138	138	137
TOTPERF	0.60703	0.36773	0.33608	-0.03006	1.00000	0.61404	0.41711
	0.0001	0.0001	0.0001	0.7263	0.0	0.0001	0.0001
	138	138	138	138	138	138	137
TOTPERS	0.41929	-0.01855	-0.00483	-0.19962	0.61404	1.00000	0.05269
	0.0001	0.8290	0.9552	0.0189	0.0001	0.0	0.5409
	138	138	138	138	138	138	137
TOTSELF	0.35718	0.44232	0.55668	0.10661	0.41711	0.05269	1.00000
	0.0001	0.0001	0.0001	0.2150	0.0001	0.5409	0.0
	137	137	137	137	137	137	137

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APPENDIX B

MULTIPLE REGRESSION ANALYSES

Table B.1
Initial stepwise regression: Coach

Stepwise Procedure for Dependent Variable TOTCOACH

Step 1 Variable TOTACHOR Entered R-square = 0.15145558 C(p) = 12.54447398

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	1	110102.81093943	110102.81093943	6.60	0.0143
Error	37	616861.54803493	16671.93373067		
Total	38	726964.35897436			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	109.55021834	133.00818993	11309.82027782	0.68	0.4154
TOTACHOR	96.82751092	37.67840866	110102.81093943	6.60	0.0143

Bounds on condition number: 1, 1

All variables left in the model are significant at the 0.1000 level.
No other variable met the 0.1000 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable TOTCOACH

Step	Variable Entered Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	TOTACHOR	1	0.1515	0.1515	12.5445	6.6041	0.0143

Table B.1
Second stepwise regression: Coach

Stepwise Procedure for Dependent Variable TOTCOACH

Step 1 Variable TOTACHOR Entered R-square = 0.15145558 C(p) = 12.54447398

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	1	110102.81093943	110102.81093943	6.60	0.0143
Error	37	616861.54803493	16671.93373067		
Total	38	726964.35897436			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	109.55021834	133.00818993	11309.82027782	0.68	0.4154
TOTACHOR	96.82751092	37.67840866	110102.81093943	6.60	0.0143

Bounds on condition number: 1, 1

Step 2 Variable OPQDECEX Entered R-square = 0.21346117 C(p) = 11.07026248

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	2	155178.65903060	77589.32951530	4.89	0.0133
Error	36	571785.69994376	15882.93610955		
Total	38	726964.35897436			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	286.94656918	167.16020241	46802.28806775	2.95	0.0946
TOTACHOR	89.53402700	37.02999949	92853.78539826	5.85	0.0208
OPQDECEX	-53.87767154	31.98175261	45075.84809118	2.84	0.1007

Bounds on condition number: 1.013859, 4.055435

Step 3 Variable OPQACHOR Entered R-square = 0.32221180 C(p) = 6.97689636

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	3	234236.49564860	78078.83188287	5.55	0.0032
Error	35	492727.86332576	14077.93895216		
Total	38	726964.35897436			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	205.39483201	161.09417924	22885.39457263	1.63	0.2107
TOTACHOR	96.14983600	34.97404912	106400.66492590	7.56	0.0094
OPQDECEX	-107.92839872	37.77335221	114931.60955049	8.16	0.0071
OPQACHOR	76.88175434	32.44295175	79057.83661799	5.62	0.0234

Bounds on condition number: 1.602667, 12.65601

Table B.1
Second stepwise regression: Coach

Step 4 Variable VERBANAL Entered R-square = 0.42150977 C(p) = 3.41316890

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	4	306422.58269395	76605.64567349	6.19	0.0007
Error	34	420541.77628041	12368.87577295		
Total	38	726964.35897436			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	251.14354075	152.18232461	33685.71934578	2.72	0.1081
TOTACHOR	111.24107738	33.37233853	137431.82685612	11.11	0.0021
OPQDECEX	-131.13713856	36.68657327	158040.11516145	12.78	0.0011
OPQACHOR	85.64885114	30.62574268	96738.65683625	7.82	0.0084
VERBANAL	-1.99975377	0.82777992	72186.08704535	5.84	0.0212

Bounds on condition number: 1.71312, 22.07133

Step 5 Variable OPQDEMP Entered R-square = 0.47604654 C(p) = 2.35743972

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	5	346068.86905917	69213.77381183	6.00	0.0005
Error	33	380895.48991519	11542.28757319		
Total	38	726964.35897436			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	87.61475999	171.45582853	3013.99088900	0.26	0.6127
TOTACHOR	108.25941031	32.27807212	129839.85732532	11.25	0.0020
OPQDECEX	-132.13124244	35.44359103	160408.54309122	13.90	0.0007
OPQACHOR	87.26740012	29.59760673	100342.00509675	8.69	0.0058
VERBANAL	-2.18702533	0.80600116	84982.24289114	7.36	0.0105
OPQDEMP	67.25586950	36.28898993	39646.28636522	3.43	0.0728

Bounds on condition number: 1.713513, 32.82048

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable TOTCOACH

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	TOTACHOR		1	0.1515	0.1515	12.5445	6.6041	0.0143
2	OPQDECEX		2	0.0620	0.2135	11.0703	2.8380	0.1007
3	OPQACHOR		3	0.1088	0.3222	6.9769	5.6157	0.0234
4	VERBANAL		4	0.0993	0.4215	3.4132	5.8361	0.0212
5	OPQDEMP		5	0.0545	0.4760	2.3574	3.4349	0.0728

Table B.2
Standard multiple regression: Coach

Model: MODEL1
Dependent Variable: TOTCOACH

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	5	329016.00936	65803.20187	5.612	0.0007
Error	34	398669.96564	11725.58722		
C Total	39	727685.97500			

Root MSE	108.28475	R-square	0.4521
Dep Mean	446.52500	Adj R-sq	0.3716
C.V.	24.25055		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	Type I SS	Type II SS	Standardized Estimate	Squared Semi-partial Corr Type I
INTERCEP	1	125.257061	170.08588801	0.736	0.4665	7975383	6359.199840	0.00000000	.
TOTACHOR	1	99.130455	31.67716468	3.129	0.0036	110443	114830	0.40213591	0.15177318
OPQDECEX	1	-127.593901	35.53332194	-3.591	0.0010	44753	151190	-0.60573105	0.06149981
OPQACHOR	1	75.560005	28.27563252	2.672	0.0115	76244	83732	0.43753711	0.10477595
VERBANAL	1	-1.863632	0.76874068	-2.424	0.0208	54477	68912	-0.32942719	0.07486336
OPQDEMP	1	69.993796	36.50833837	1.917	0.0636	43099	43099	0.24751883	0.05922779

Variable	DF	Squared Partial Corr Type I	Squared Semi-partial Corr Type II	Squared Partial Corr Type II
INTERCEP	1	.	.	.
TOTACHOR	1	0.15177318	0.15780189	0.22362255
OPQDECEX	1	0.07250396	0.20776807	0.27496080
OPQACHOR	1	0.13317956	0.11506676	0.17357390
VERBANAL	1	0.10977820	0.09470023	0.14737956
OPQDEMP	1	0.09756053	0.05922779	0.09756053

Stepwise Procedure for Dependent Variable TOTCSR

Step 1 Variable TOTHI Entered R-square = 0.05409361 C(p) = -1.37888126

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	1	26768.62282369	26768.62282369	6.29	0.0136
Error	110	468088.80574774	4255.35277952		
Total	111	494857.42857143			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	273.87812666	27.29620958	428396.16993615	100.67	0.0001
TOTHI	19.97232571	7.96312276	26768.62282369	6.29	0.0136

Bounds on condition number: 1, 1

Step 2 Variable CSHI Entered R-square = 0.08160373 C(p) = -2.47978032

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	2	40382.21228285	20191.10614143	4.84	0.0097
Error	109	454475.21628857	4169.49739714		
Total	111	494857.42857143			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	251.01842391	29.83452853	295159.35012010	70.79	0.0001
CSHI	18.18902455	10.06618570	13613.58945916	3.27	0.0735
TOTHI	18.35573864	7.93299126	22323.04763602	5.35	0.0226

Bounds on condition number: 1.012882, 4.051529

Step 3 Variable VERBHI Entered R-square = 0.10973582 C(p) = -3.65078608

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	3	54303.58466503	18101.19488834	4.44	0.0056
Error	108	440553.84390640	4079.20225839		
Total	111	494857.42857143			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	263.70803618	30.29862161	309012.62683778	75.75	0.0001
CSHI	18.67593354	9.96007980	14342.14941769	3.52	0.0635
TOTHI	18.04907908	7.84837787	21573.74427670	5.29	0.0234
VERBHI	-0.43355191	0.23468628	13921.37238217	3.41	0.0674

Bounds on condition number: 1.013592, 9.083889

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable TOTCSR

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	TOTHI		1	0.0541	0.0541	-1.3789	6.2906	0.0136
2	CSHI		2	0.0275	0.0816	-2.4798	3.2650	0.0735
3	VERBHI		3	0.0281	0.1097	-3.6508	3.4128	0.0674

Table B.4
Standard multiple regression: Csr

Model: MODEL1
Dependent Variable: TOTCSR

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	54134.96905	18044.98968	4.423	0.0056
Error	109	444710.03980	4079.90862		
C Total	112	498845.00885			

Root MSE	63.87416	R-square	0.1085
Dep Mean	341.13274	Adj R-sq	0.0840
C.V.	18.72414		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	Type I SS	Type II SS	Standardized Estimate	Squared Semi-partial Corr Type I
INTERCEP	1	260.143358	30.09471283	8.644	0.0001	13149985	304857	0.00000000	.
CSHI	1	19.215946	9.94656257	1.932	0.0560	19156	15227	0.17606057	0.03840009
VERBHI	1	-0.388423	0.23040816	-1.686	0.0947	11824	11595	-0.15256505	0.02370320
TOTHI	1	18.645749	7.82676314	2.382	0.0189	23155	23155	0.21695865	0.04641732

Variable	DF	Squared Partial Corr Type I	Squared Semi-partial Corr Type II	Squared Partial Corr Type II
INTERCEP	1	.	.	.
CSHI	1	0.03840009	0.03052547	0.03310771
VERBHI	1	0.02464975	0.02324332	0.02541024
TOTHI	1	0.04949087	0.04641732	0.04949087

Table B.5
Stepwise regression: Pa

Stepwise Procedure for Dependent Variable TOTPA

Step 1 Variable TOTCOOP Entered R-square = 0.09267181 C(p) = 10.11446437

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	1	39370.46978648	39370.46978648	12.36	0.0006
Error	121	385467.15622978	3185.67897711		
Total	122	424837.62601626			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	331.37546901	18.79445610	990337.43595225	310.87	0.0001
TOTCOOP	-17.69950835	5.03473839	39370.46978648	12.36	0.0006

Bounds on condition number: 1, 1

Step 2 Variable CLASSHI Entered R-square = 0.14491925 C(p) = 4.67955705

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	2	61567.15081186	30783.57540593	10.17	0.0001
Error	120	363270.47520440	3027.25396004		
Total	122	424837.62601626			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	290.96331503	23.63045423	458966.71261583	151.61	0.0001
CLASSHI	0.64684018	0.23887868	22196.68102539	7.33	0.0078
TOTCOOP	-16.01277780	4.94732392	31713.30598215	10.48	0.0016

Bounds on condition number: 1.016108, 4.064433

Step 3 Variable CCSQPERF Entered R-square = 0.17494143 C(p) = 2.40734669

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	3	74321.69992798	24773.89997599	8.41	0.0001
Error	119	350515.92608828	2945.51198394		
Total	122	424837.62601626			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	242.04159002	33.10638733	157440.76995379	53.45	0.0001
CCSQPERF	12.20166353	5.86363444	12754.54911612	4.33	0.0396
CLASSHI	0.62884618	0.23579012	20950.69489787	7.11	0.0087
TOTCOOP	-13.78244534	4.99638739	22413.05951951	7.61	0.0067

Bounds on condition number: 1.065123, 9.405133

Table B.5
Stepwise regression: Pa

Step 4 Variable CCSQISEN Entered R-square = 0.19919289 C(p) = 0.95631906

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	4	84624.63394147	21156.15848537	7.34	0.0001
Error	118	340212.99207479	2883.16094979		
Total	122	424837.62601626			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	232.10408444	33.17328901	141142.36443707	48.95	0.0001
CCSQPERF	11.53770974	5.81186405	11362.58672663	3.94	0.0494
CLASSHI	0.57521035	0.23500029	17273.70326652	5.99	0.0158
TOTCOOP	-22.18693995	6.64845932	32108.62230255	11.14	0.0011
CCSQISEN	13.19345399	6.97931004	10302.93401348	3.57	0.0612

Bounds on condition number: 1.926732, 23.37185

Step 5 Variable NUMISP Entered R-square = 0.22284603 C(p) = -0.40956625

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	5	94673.37824964	18934.67564993	6.71	0.0001
Error	117	330164.24776662	2821.91664758		
Total	122	424837.62601626			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	213.32412283	34.29480208	109186.14102766	38.69	0.0001
CCSQPERF	11.80091414	5.75149621	11879.92795890	4.21	0.0424
CLASSHI	0.48194815	0.23768591	11602.13551918	4.11	0.0449
NUMISP	0.42742510	0.22650418	10048.74430818	3.56	0.0616
TOTCOOP	-21.85765244	6.57978106	31140.69687193	11.04	0.0012
CCSQISEN	14.31689021	6.93040260	12042.72149417	4.27	0.0411

Bounds on condition number: 1.928088, 34.86545

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable TOTPA

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	TOTCOOP		1	0.0927	0.0927	10.1145	12.3586	0.0006
2	CLASSHI		2	0.0522	0.1449	4.6796	7.3323	0.0078
3	CCSQPERF		3	0.0300	0.1749	2.4073	4.3302	0.0396
4	CCSQISEN		4	0.0243	0.1992	0.9563	3.5735	0.0612
5	NUMISP		5	0.0237	0.2228	-0.4096	3.5610	0.0616

Table B.6
Standard multiple regression: Pa

Model: MODEL1
Dependent Variable: TOTPA

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	5	89152.79166	17830.55833	6.249	0.0001
Error	119	339539.65634	2853.27442		
C Total	124	428692.44800			

Root MSE	53.41605	R-square	0.2080
Dep Mean	268.30400	Adj R-sq	0.1747
C.V.	19.90878		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	Type I SS	Type II SS	Standardized Estimate	Squared Semi-partial Corr Type I
INTERCEP	1	232.310690	32.81086737	7.080	0.0001	8998380	143036	0.00000000	.
CLASSHI	1	0.439359	0.23784265	1.847	0.0672	26638	9736.513265	0.15732260	0.06213779
CCSQPERF	1	9.990643	5.69299492	1.755	0.0818	18171	8787.166202	0.14664974	0.04238766
TOTCOOP	1	-22.951921	6.55038542	-3.504	0.0006	27490	35031	-0.39716825	0.06412605
CCSQISEN	1	13.478372	6.94062990	1.942	0.0545	9469.461133	10760	0.21626493	0.02208917
NUMISP	1	0.361580	0.22477024	1.609	0.1103	7383.704521	7383.704521	0.13572378	0.01722378

Variable	DF	Squared Partial Corr Type I	Squared Semi-partial Corr Type II	Squared Partial Corr Type II
INTERCEP	1	.	.	.
CLASSHI	1	0.06213779	0.02271212	0.02787626
CCSQPERF	1	0.04519604	0.02049760	0.02522679
TOTCOOP	1	0.07161125	0.08171506	0.09352218
CCSQISEN	1	0.02657029	0.02510006	0.03071713
NUMISP	1	0.02128339	0.01722378	0.02128339

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APPENDIX C

FAIRNESS ANALYSIS

Table C.1
Regression of composite Csr criterion on combination of predictors

Model: MODEL1
Dependent Variable: TOTCSR

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	54134.96905	18044.98968	4.423	0.0056
Error	109	444710.03980	4079.90862		
C Total	112	498845.00885			

Root MSE	63.87416	R-square	0.1085
Dep Mean	341.13274	Adj R-sq	0.0840
C.V.	18.72414		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	260.143358	30.09471283	8.644	0.0001
CSHI	1	19.215946	9.94656257	1.932	0.0560
VERBHI	1	-0.388423	0.23040816	-1.686	0.0947
TOTHI	1	18.645749	7.82676314	2.382	0.0189

Table C.2
Regression of composite Csr on combination of predictors

Model: MODEL1
Dependent Variable: TOTCSR

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	54134.96905	54134.96905	13.512	0.0004
Error	111	444710.03980	4006.39675		
C Total	112	498845.00885			

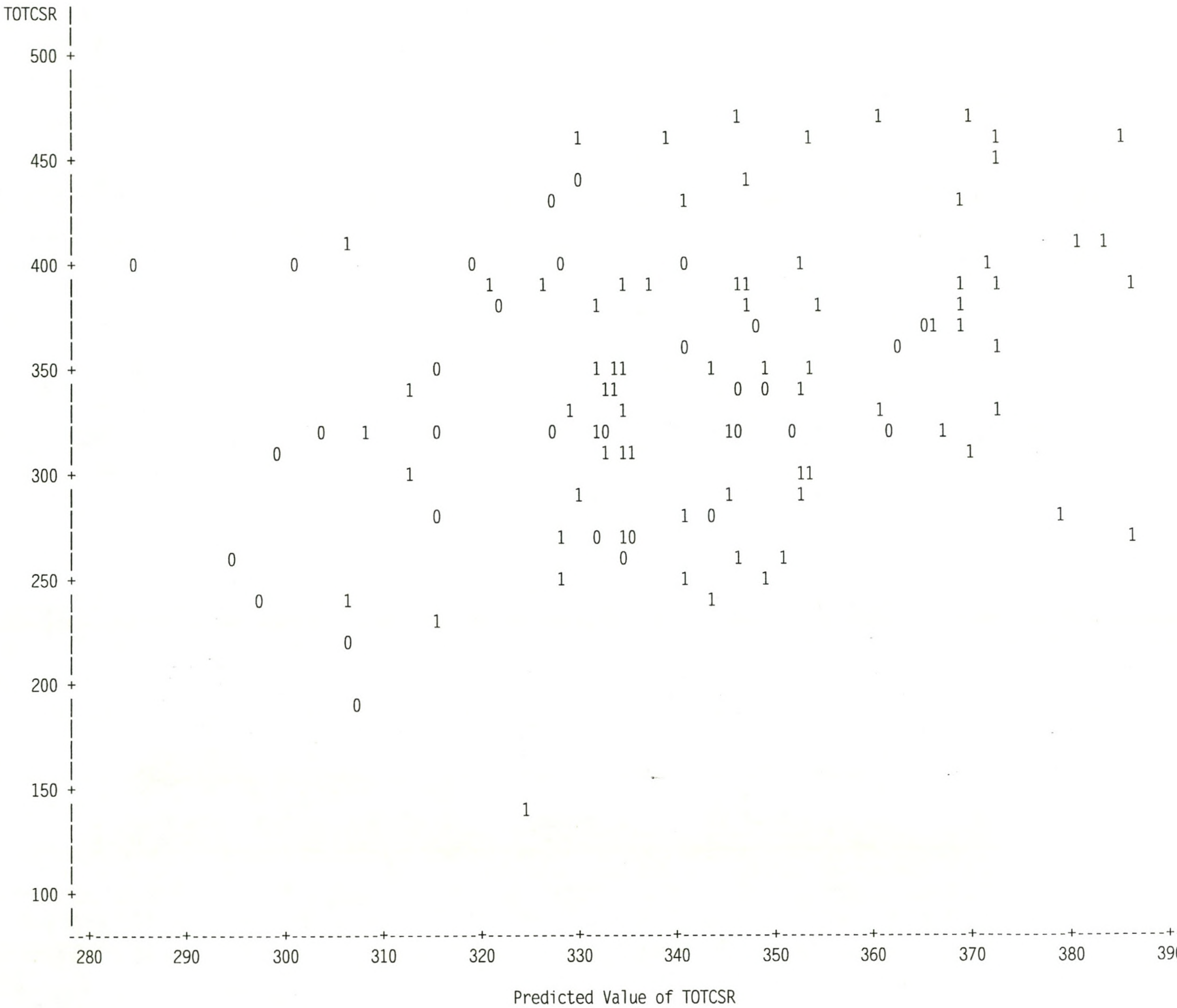
Root MSE	63.29610	R-square	0.1085
Dep Mean	341.13274	Adj R-sq	0.1005
C.V.	18.55468		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	Variable Label
INTERCEP	1	-4.71232E-11	92.99370269	-0.000	1.0000	Intercept
YHAT	1	1.000000	0.27204330	3.676	0.0004	Predicted Value of TOTCSR

Figure C.1
Plot of composite Csr criterion by linear combination of predictors
with group membership distinguished

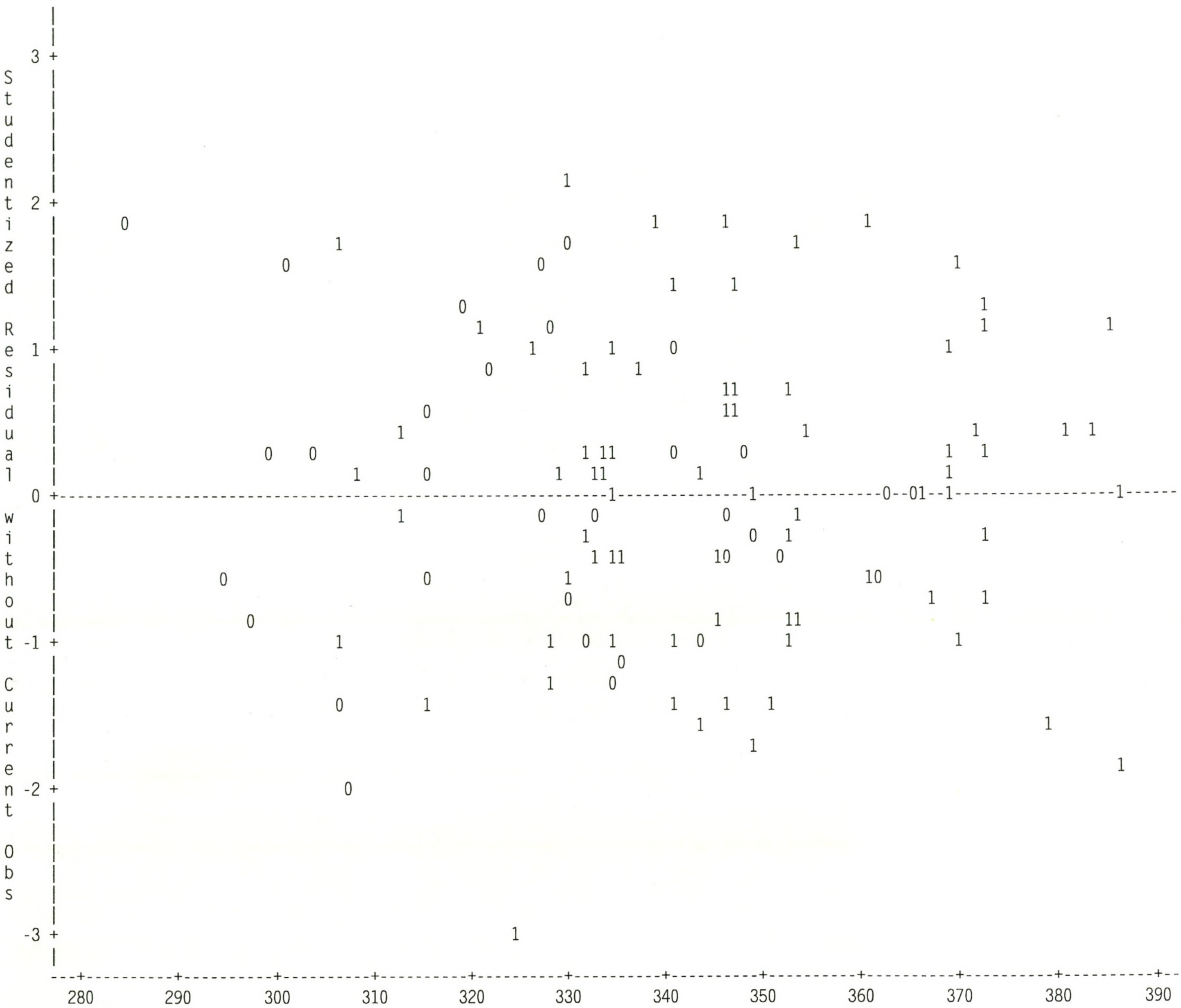
Plot of TOTCSR*YHAT. Symbol is value of GROUP.



NOTE: 34 obs had missing values. 6 obs hidden.

Figure C.2
Plot of residuals by linear combination of predictors
with group membership distinguished

Plot of RESID*YHAT. Symbol is value of GROUP.



NOTE: 34 obs had missing values. 4 obs hidden.

Table C.3
Comparison of mean residuals across groups via anova

Analysis of Variance Procedure
Class Level Information

Class	Levels	Values
GROUP	2	black white

Number of observations in data set = 147

NOTE: Due to missing values, only 113 observations can be used in this analysis.

Table C.3
Comparison of mean residuals across groups via anova

Analysis of Variance Procedure

Dependent Variable: RESID   Studentized Residual without Current Obs

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	0.03709116	0.03709116	0.04	0.8502
Error	111	114.90453995	1.03517604		
Corrected Total	112	114.94163111			

	R-Square	C.V.	Root MSE		RESID Mean
	0.000323	9999.99	1.01743601		0.00027570

Source	DF	Anova SS	Mean Square	F Value	Pr > F
GROUP	1	0.03709116	0.03709116	0.04	0.8502

Table C.3
Comparison of mean residuals across groups via anova

Analysis of Variance Procedure

Level of GROUP	N	RESID Mean	RESID SD
black	34	-0.02734089	0.97330186
white	79	0.01216132	1.03554207

Table C.4
Regression of the composite Csr criterion on yhat by group

---------- GROUP=black ----------

Model: MODEL1
Dependent Variable: TOTCSR

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	4657.28518	4657.28518	1.260	0.2700
Error	32	118254.59718	3695.45616		
C Total	33	122911.88235			

Root MSE	60.79026	R-square	0.0379
Dep Mean	326.05882	Adj R-sq	0.0078
C.V.	18.64396		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	Variable Label
INTERCEP	1	138.100480	167.75270838	0.823	0.4165	Intercept
YHAT	1	0.573227	0.51061545	1.123	0.2700	Predicted Value of TOTCSR

Table C.4
Regression of the composite Csr criterion on yhat by group

-- GROUP=white --

Model: MODEL1
Dependent Variable: TOTCSR

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	41926.02757	41926.02757	9.996	0.0022
Error	77	322956.58002	4194.24130		
C Total	78	364882.60759			

Root MSE	64.76296	R-square	0.1149
Dep Mean	347.62025	Adj R-sq	0.1034
C.V.	18.63038		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	Variable Label
INTERCEP	1	-52.896305	126.88858193	-0.417	0.6779	Intercept
YHAT	1	1.154793	0.36524885	3.162	0.0022	Predicted Value of TOTCSR

Table C.5
Regression of criterion on yhat, group and group*yhat interaction
(fitting of satuarated regression model)

General Linear Models Procedure

Number of observations in data set = 147

NOTE: Due to missing values, only 113 observations can be used in this analysis.

Table C.5
Regression of criterion on yhat, group and group*yhat interaction
(fitting of satuarated regression model)

General Linear Models Procedure

Dependent Variable: TOTCSR

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	57633.83165244	19211.27721748	4.75	0.0038
Error	109	441211.17719712	4047.80896511		
Corrected Total	112	498845.00884956			

	R-Square	C.V.	Root MSE	TOTCSR Mean
	0.115535	18.65033	63.62239358	341.13274336

Source	DF	Type I SS	Mean Square	F Value	Pr > F
YHAT	1	54134.96905128	54134.96905128	13.37	0.0004
GROUP	1	194.67799526	194.67799526	0.05	0.8268
YHAT*GROUP	1	3304.18460590	3304.18460590	0.82	0.3683

Source	DF	Type II SS	Mean Square	F Value	Pr > F
YHAT	1	4657.28517683	4657.28517683	1.15	0.2858
GROUP	1	3184.95316080	3184.95316080	0.79	0.3770
YHAT*GROUP	1	3304.18460590	3304.18460590	0.82	0.3683

Parameter	Estimate	T for H0: Parameter=0	Pr > |T|	Std Error of Estimate
INTERCEPT	138.1004797	0.79	0.4332	175.5680628
YHAT	0.5732266	1.07	0.2858	0.5344043
GROUP	-190.9967846	-0.89	0.3770	215.3200813
YHAT*GROUP	0.5815660	0.90	0.3683	0.6436902

Table C.6
Regression of the criterion on yhat and group
(reduced regression model)

General Linear Models Procedure

Number of observations in data set = 147

NOTE: Due to missing values, only 113 observations can be used in this analysis.

Table C.6
Regression of the criterion on yhat and group
(reduced regression model)

General Linear Models Procedure

Dependent Variable: TOTCSR

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	54329.64704653	27164.82352327	6.72	0.0018
Error	110	444515.36180303	4041.04874366		
Corrected Total	112	498845.00884956			

	R-Square	C.V.	Root MSE	TOTCSR Mean
	0.108911	18.63475	63.56924369	341.13274336

Source	DF	Type I SS	Mean Square	F Value	Pr > F
YHAT	1	54134.96905128	54134.96905128	13.40	0.0004
GROUP	1	194.67799526	194.67799526	0.05	0.8267

Source	DF	Type II SS	Mean Square	F Value	Pr > F
YHAT	1	43279.12814485	43279.12814485	10.71	0.0014
GROUP	1	194.67799526	194.67799526	0.05	0.8267

Parameter	Estimate	T for H0: Parameter=0	Pr > |T|	Std Error of Estimate
INTERCEPT	6.662650124	0.07	0.9460	98.20424689
YHAT	0.974079581	3.27	0.0014	0.29764750
GROUP	3.117732031	0.22	0.8267	14.20454728

Table C.7
Regression of the criterion on yhat and yhat*group
(reduced regression model)

General Linear Models Procedure

Number of observations in data set = 147

NOTE: Due to missing values, only 113 observations can be used in this analysis.

Table C.7
Regression of the criterion on yhat and yhat*group
(reduced regression model)

General Linear Models Procedure

Dependent Variable: TOTCSR

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	54448.87849164	27224.43924582	6.74	0.0017
Error	110	444396.13035792	4039.96482144		
Corrected Total	112	498845.00884956			

R-Square	C.V.	Root MSE	TOTCSR Mean
0.109150	18.63225	63.56071760	341.13274336

Source	DF	Type I SS	Mean Square	F Value	Pr > F
YHAT	1	54134.96905128	54134.96905128	13.40	0.0004
YHAT*GROUP	1	313.90944036	313.90944036	0.08	0.7810

Source	DF	Type II SS	Mean Square	F Value	Pr > F
YHAT	1	38597.55900797	38597.55900797	9.55	0.0025
YHAT*GROUP	1	313.90944036	313.90944036	0.08	0.7810

Parameter	Estimate	T for H0: Parameter=0	Pr > |T|	Std Error of Estimate
INTERCEPT	11.11676709	0.11	0.9130	101.5419763
YHAT	0.95899986	3.09	0.0025	0.3102612
YHAT*GROUP	0.01183518	0.28	0.7810	0.0424582

Table C.8
Simple regression of composite Csr criterion on yhat via proc glm

General Linear Models Procedure

Number of observations in data set = 147

NOTE: Due to missing values, only 113 observations can be used in this analysis.

Table C.8
Simple regression of composite Csr criterion on yhat via proc glm

General Linear Models Procedure

Dependent Variable: TOTCSR

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	54134.96905128	54134.96905128	13.51	0.0004
Error	111	444710.03979828	4006.39675494		
Corrected Total	112	498845.00884956			

	R-Square	C.V.	Root MSE	TOTCSR Mean
	0.108521	18.55468	63.29610379	341.13274336

Source	DF	Type I SS	Mean Square	F Value	Pr > F
YHAT	1	54134.96905128	54134.96905128	13.51	0.0004

Source	DF	Type II SS	Mean Square	F Value	Pr > F
YHAT	1	54134.96905128	54134.96905128	13.51	0.0004

Parameter	Estimate	T for H0: Parameter=0	Pr > |T|	Std Error of Estimate
INTERCEPT	-0.000000000	-0.00	1.0000	92.99370269
YHAT	1.000000000	3.68	0.0004	0.27204330

Table C.9
Descriptive statsistics for composite Csr criterion

Univariate Procedure

Variable=TOTCSR

Moments

N	114	Sum Wgts	114
Mean	340.9912	Sum	38873
Std Dev	66.45932	Variance	4416.841
Skewness	-0.12255	Kurtosis	-0.16892
USS	13754455	CSS	499103
CV	19.49004	Std Mean	6.224485
T:Mean=0	54.78224	Pr>|T|	0.0001
Num ^= 0	114	Num > 0	114
M(Sign)	57	Pr>=|M|	0.0001
Sgn Rank	3277.5	Pr>=|S|	0.0001
W:Normal	0.977608	Pr<W	0.3641

Quantiles(Def=5)

100% Max	473	99%	467
75% Q3	392	95%	456
50% Med	338	90%	432
25% Q1	294	10%	257
0% Min	139	5%	241
		1%	186
Range	334		
Q3-Q1	98		
Mode	316		

Extremes

Lowest	Obs	Highest	Obs
139(	51)	460(	58)
186(	34)	464(	99)
217(	23)	465(	54)
230(	66)	467(	92)
240(	60)	473(	120)

Missing Value	.
Count	33
% Count/Nobs	22.45

```
 Stem Leaf                      #         Boxplot                     Normal Probability Plot
   46 04573                     5            |             470+                                           *+** *  *
   44 17556                     5            |                |                                        **+*
   42 5928                      4            |                |                                      **+
   40 0014044                   7            |                |                                   ***
   38 046689922344557          15         +-----+             |                               *****
   36 35567799                  8         |     |             |                             **+
   34 15569333455              11         |  +  |             |                          +***
   32 011122335691456799       18         *-----*             |                       ****
   30 002591136669             12         |     |             |                    ***
   28 0018904                   7         +-----+             |                 +**
   26 58991229                  8            |                |              +***
   24 0136906788               10            |                |         ******
   22 0                         1            |                |       *+++
   20 7                         1            |                |     +*+
   18 6                         1            |                |  ++*
   16                                                         |+
   14                                                         |
   12 9                         1            0             130+*
      ----+----+----+----+                                    +----+----+----+----+----+----+----+----+----+----+
 Multiply Stem.Leaf by 10**+1                                      -2        -1         0        +1        +2
```

Table C.10
Correlation between linear predictor composite and composite
Csr criterion

-- GROUP=black --

Correlation Analysis

2 'VAR' Variables: TOTCSR YHAT

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum	Label
TOTCSR	35	326.028571	60.125597	11411	186.000000	438.000000	
YHAT	47	329.180312	21.180921	15471	284.800142	369.274019	Predicted Value of TOTCSR

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCSR	YHAT
TOTCSR	1.00000 0.0 35	0.19466 0.2700 34
YHAT Predicted Value of TOTCSR	0.19466 0.2700 34	1.00000 0.0 47

Table C.10
Correlation between linear predictor composite and composite
Csr criterion

------ GROUP=white ------

Correlation Analysis

2 'VAR' Variables: TOTCSR YHAT

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum	Label
TOTCSR	79	347.620253	68.395776	27462	139.000000	473.000000	
YHAT	98	347.093824	19.544350	34015	306.163389	386.366077	Predicted Value of TOTCSR

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / Number of Observations

	TOTCSR	YHAT
TOTCSR	1.00000	0.33897
	0.0	0.0022
	79	79
YHAT	0.33897	1.00000
Predicted Value of TOTCSR	0.0022	0.0
	79	98

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